Text Classification Using Classic Machine Learning

Week 3: Neural Networks and Word-Embeddings

Dr. Philipp K. Masur

Visualization of a fully connected neural network, version 1

SO WHAT ARE WE ACTUALLY TALKING ABOUT?

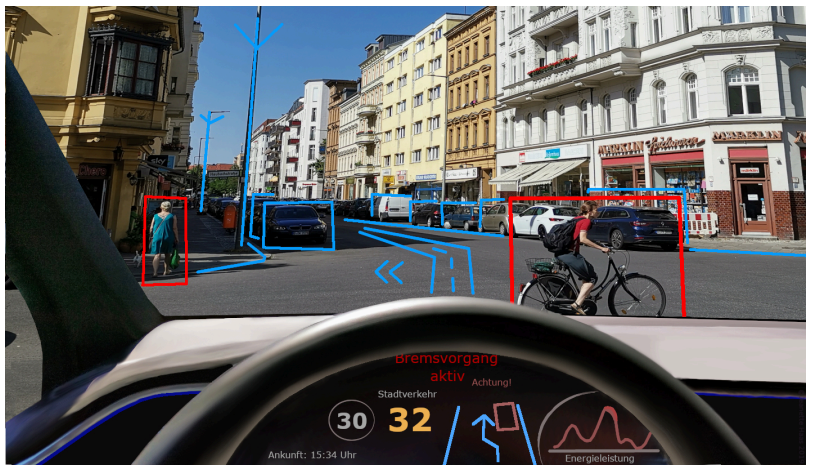
- Machine learning is the study of computer algorithms that can **improve automatically** through experience and by the use of data
- Due to the “black box” nature of the algorithm’s operations, it is often seen as a form of **artificial intelligence**

Source: qlik

SOME SUCCESS STORIES

Successful machine learning in practical contexts:

- Identification of spam messages in mails
- Segmentation of customers for targeted advertising
- Weather forecasts and long-term climate changes
- Reduction of fraudulent credit card transactions
- Prediction of election outcomes
- Auto-piloting and self-driving cars
- Face recognition
- Discovery of genetic sequences linked to diseases
- ….



CONTENT OF THIS LECTURE

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   2.2. General Idea behind Neural Networks
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3. More Complex Text Representations: Word-Embeddings
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What is machine learning?

Understanding Supervised Machine Learning Approaches

DEDUCTIVE VS. INDUCTIVE APPROACHES

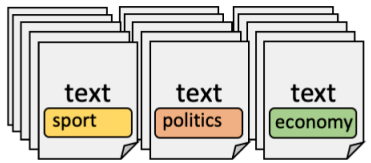
- In the previous lecture, we talked about deductive approaches (e.g., dictionary approaches)
- These are **deterministic** and are based on a priori text theory (e.g., happy → positive, hate → negative)
- Yet, natural language is often ambiguous and a **probabilistic** coding may be better
- Dictionary-based or generally rule-based approaches are not very similar to manual coding; a human being assesses much more than just a list of words
- Inductive approaches promise to combine the scalability of automatic coding with the validity of manual coding

SUPERVISED VS. UNSUPERVISED APPROACHES

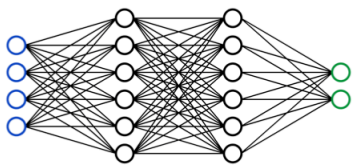
	Rule-Based Analyses	Unsupervised Machine Learning	Supervised Machine Learning	Semi-Supervised Training and Transfer Learning
Description	Code/annotate unlabeled texts based on keywords, expressions or concepts based on pre-defined word lists	Finding clusters or patterns of words that co-occur in unlabeled texts	Training a model on already labeled texts (*training data*), validate it (on labeled *test data*) to then annotate unlabeled text (unlabeled *new data*)	Training a model on a large corpus in a semi-supervised fashion (e.g., word prediction in random word masking tasks) to "learn the language". Resulting model then completes a completely new task (e.g., labeling a text) without further training
Logic	*"if word X occurs, the text means Y"*	*"these words form a pattern, which I think means X"*	*"text X is like other texts in the training data that were labeled negative, so X is probably also negative"*	*"Based on the relationships between words, phrases, and contexts learned from vast amounts of text data, the model understands that text X shares similarities with texts that tend to be labeled as negative, so X is likely negative."*
Meaning assignment	Meaning of text-word associations is assigned by researcher a priori	Meaning is assigned a posteriori by the researcher by interpreting the resulting clusters of words	Meaning of text-word-associations is generalized from human coding of the training material	Meaning is automatically provided by the model
Examples	• Dictionary approaches	• Unsupervised topic modeling	• Training a text classifier using algorithms such as Naïve Bayes, SVM, neural networks	• Text classification using pre-trained large language models (e.g., GPT, Llama, Claude…)

EXAMPLE OF SUPERVISED TEXT CLASSIFICATION

Step 1
We manually code a comparatively small set of newspaper articles (say N = 1,000) and annotate their topic (e.g., sport, politics, economy, weather,...)

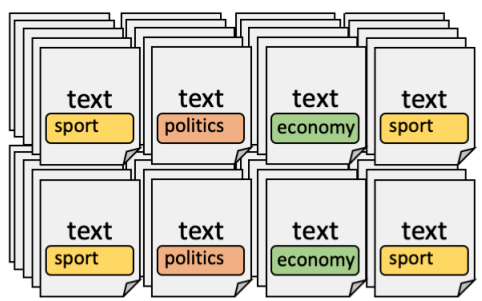


Step 2
We then train a machine learning model on a portion of this hand-coded data, using the topic as the outcome of interest and the text features of the documents as the predictors. in other words, we let the machine learning algorithm figure out the relation between text features and the topic)

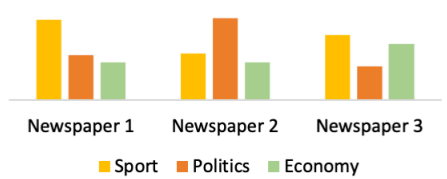


Step 3
We evaluate the effectiveness of the machine learning model via cross-validation, i.e., we test its performance on the held-out portion of the hand-coded data (our gold standard).

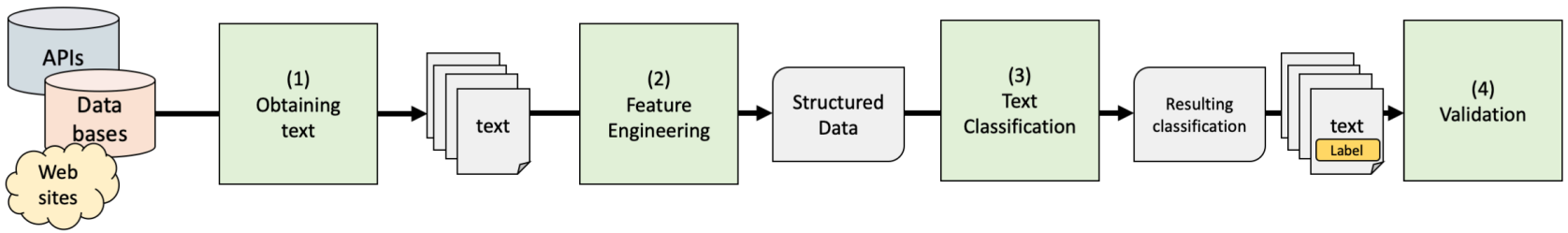
Step 4
Once you have trained a model with sufficient predictive accuracy (high performance score),we apply the resulting classifier to the remaining the newspaper articles that have never been hand-coded (e.g., N > 100,000) to get their (predicted) topics.



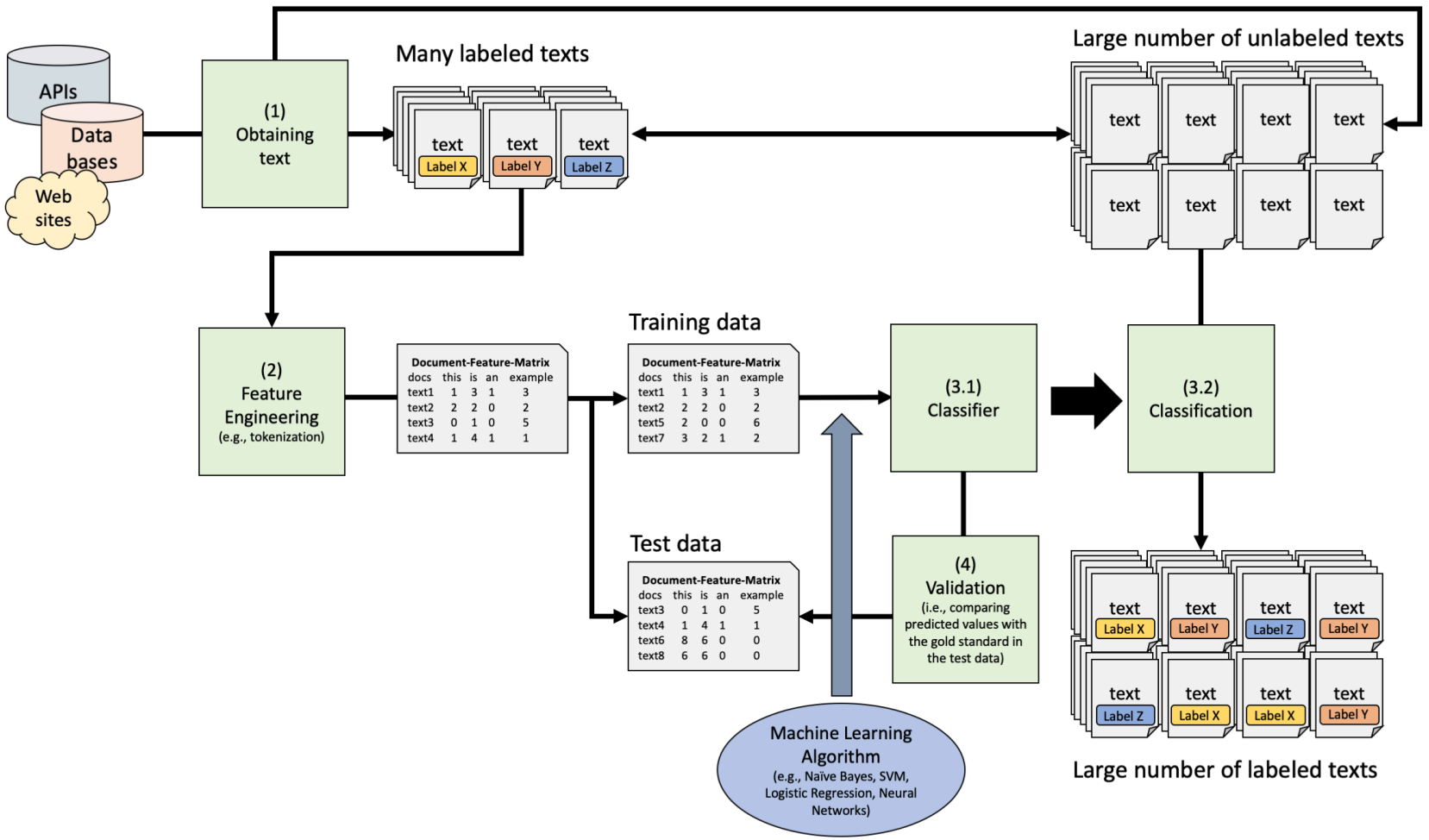
Step 5
We calculate and plot the distribution of topics for different newspapers at different times, etc.



GENERAL TEXT CLASSIFICATION PIPELINE

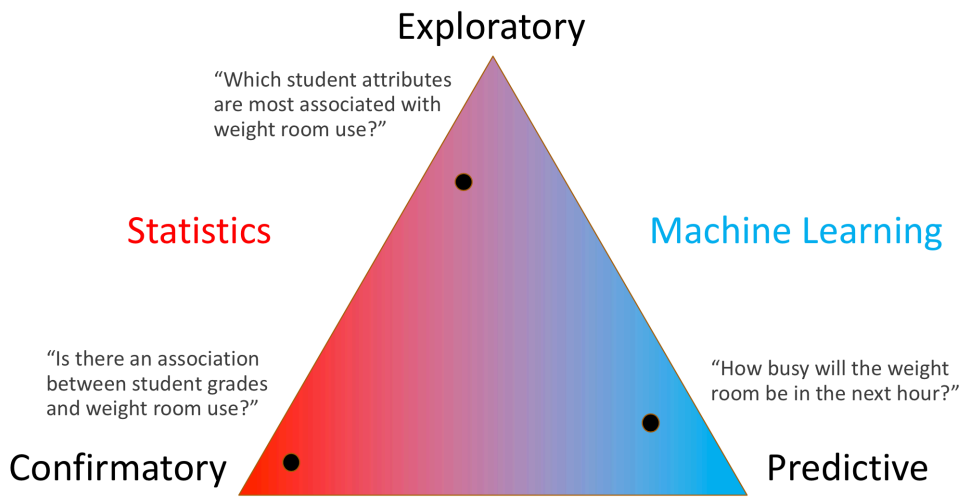


SUPERVISED TEXT CLASSIFICATION PIPELINE



STATISTICAL MODELING VS. SUPERVISED MACHINE LEARNING

- **Machine learning**, many people joke, is nothing but a fancy name for **statistics**.
- There is some truth to this: the term “logistic regression” will sound familiar to both statisticians and machine learning practitioners.
- Still, there are some differences between traditional statistical approaches and the machine learning approach, even if some of the same mathematical tools are used.



Source: Demetri Pananos/stackoverflow

STATISTICAL MODELING

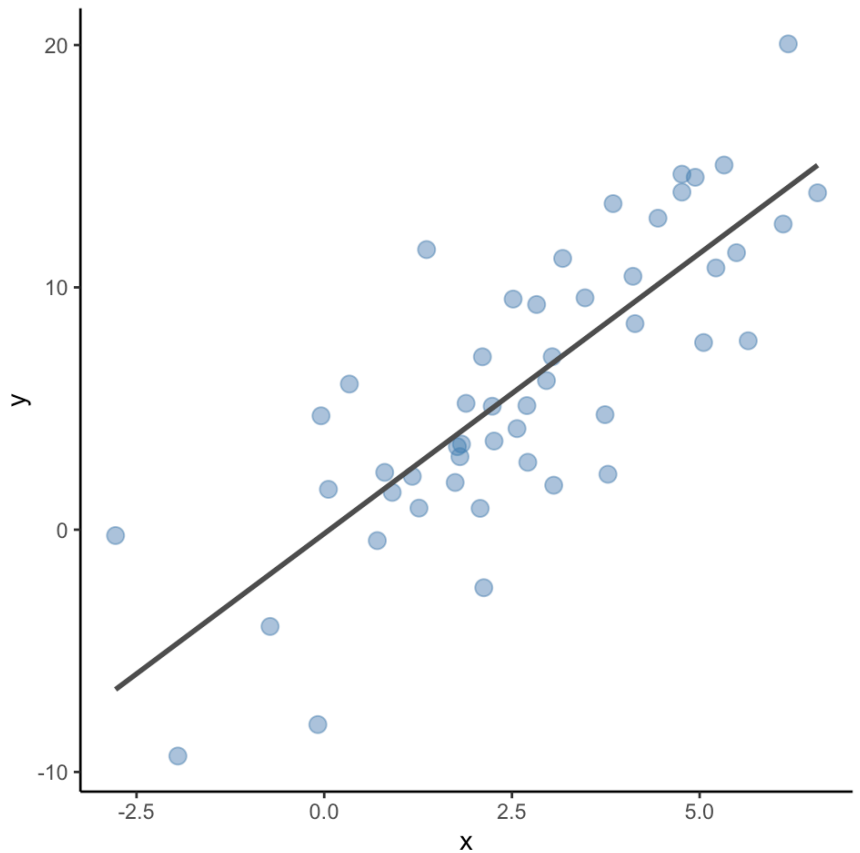
- Is about understanding the relationship between one (or several) predictor(s) and an outcome variable
- Learn f so you can predict y from x:

$$y = f(x)$$

- In a linear regression model, we try to findt he best fitting "line" that best predicts y based on x:

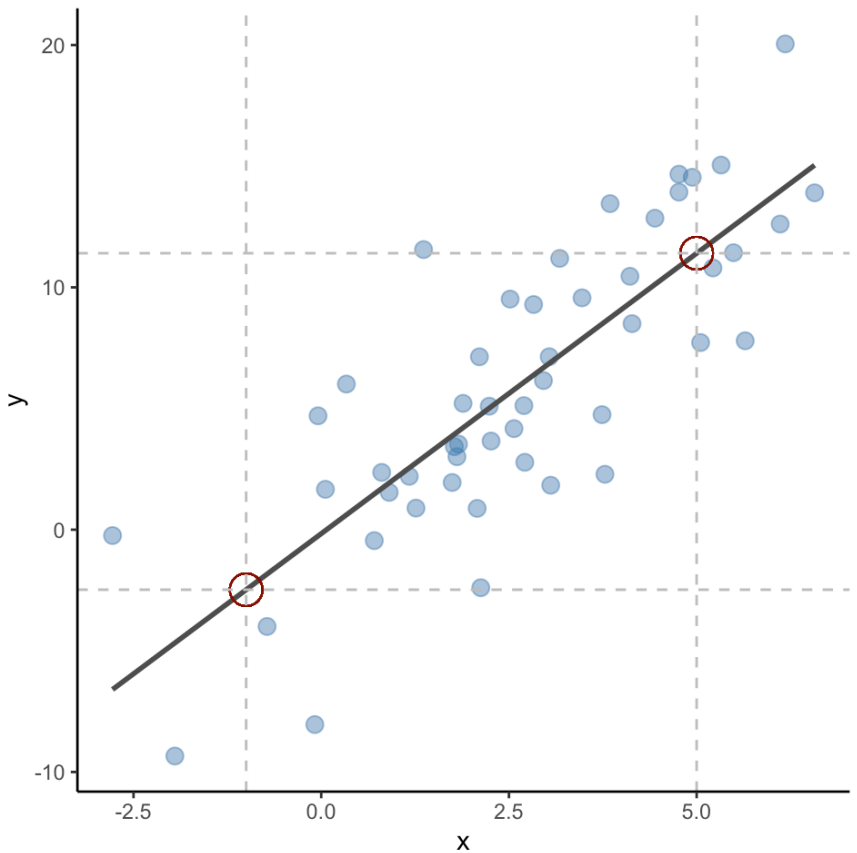
$$y = -0.16 + 2.31 * x + \epsilon$$

- We then say: when x increases by 1 unit,y increases by 2.31 units.



MACHINE LEARNING

- Machine learning less about not understanding, but about maximizing prediction
- A statistical model can be used to predict most likely y values based on new x data.
- For example, despite not being in the data, $x = -1$ should be $y = -2.47; x = 5$ should be $y = 11.41$ based on the fitted line
- In other words, machine learning doesn't focus on explanation, but emphasizes prediction



DIFFERENCES IN LANGUAGE

machine learning lingo	statistics lingo
feature	independent variable
label	dependent variable
labeled dataset	dataset with both independent and dependent variables
to train a model	to estimate
classifier (classification)	model to predict nominal outcomes
to annotate	to (manually) code (content analysis)

Source: van Atteveldt et al., 2021

DIFFERENCES IN GOALS

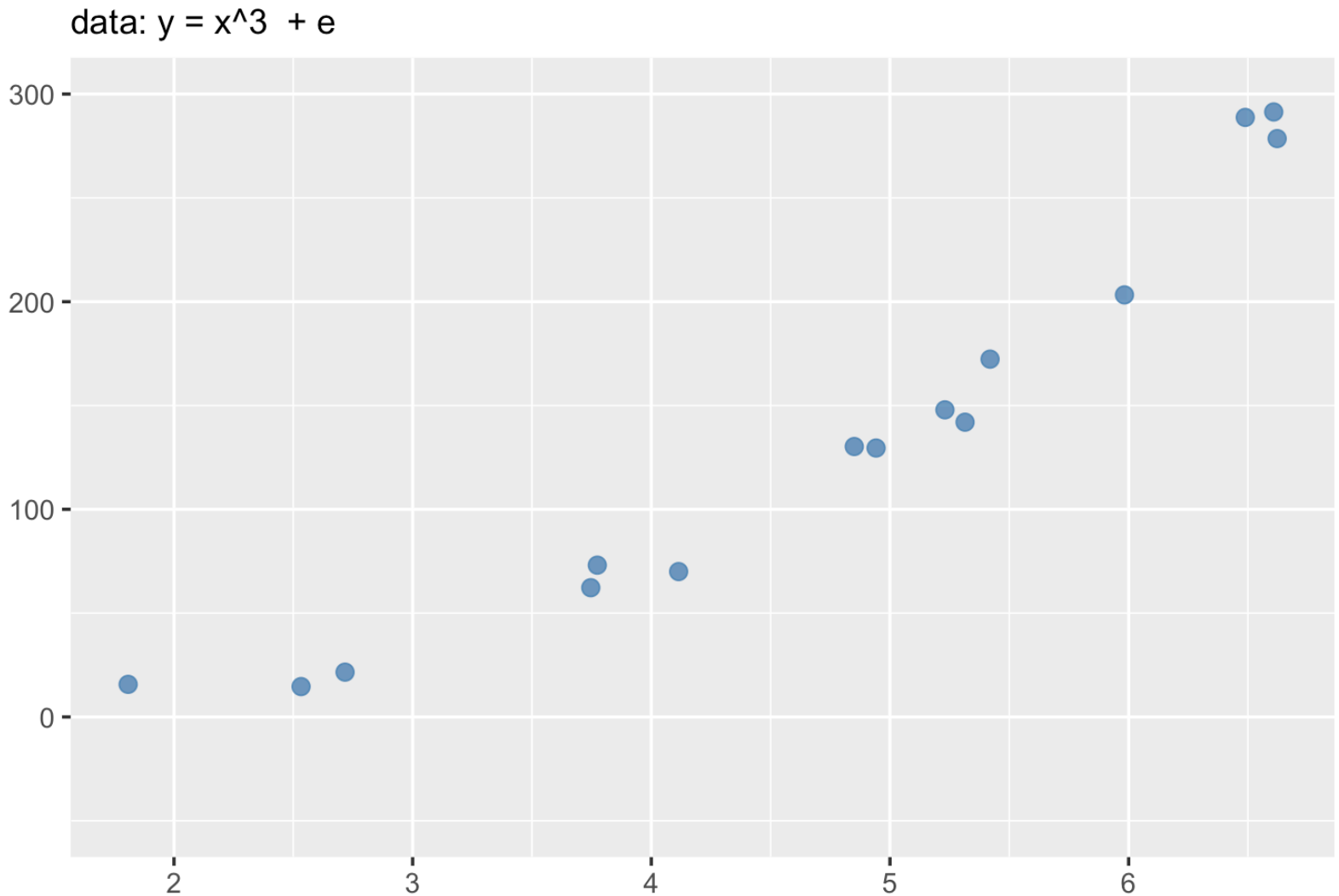
- Goal of statistical modeling: explaining/understanding
  - Serves to make inferences about a population ("Does X relate to Y?")
  - Doesn't use too many variables to avoid the difficulty of interpreting too many parameters
  - Requires interpretable parameters
- Goal of machine learning: best possible prediction
  - make generalizable predictions ("How to best predict Y?")
  - We do not care about the actual values of the coefficients, we just need them for our prediction
  - We will often have so many of them that we do not even bother to report them

Note: Machine learning models often have 1000's of colinear independent variables and can have many latent variables!

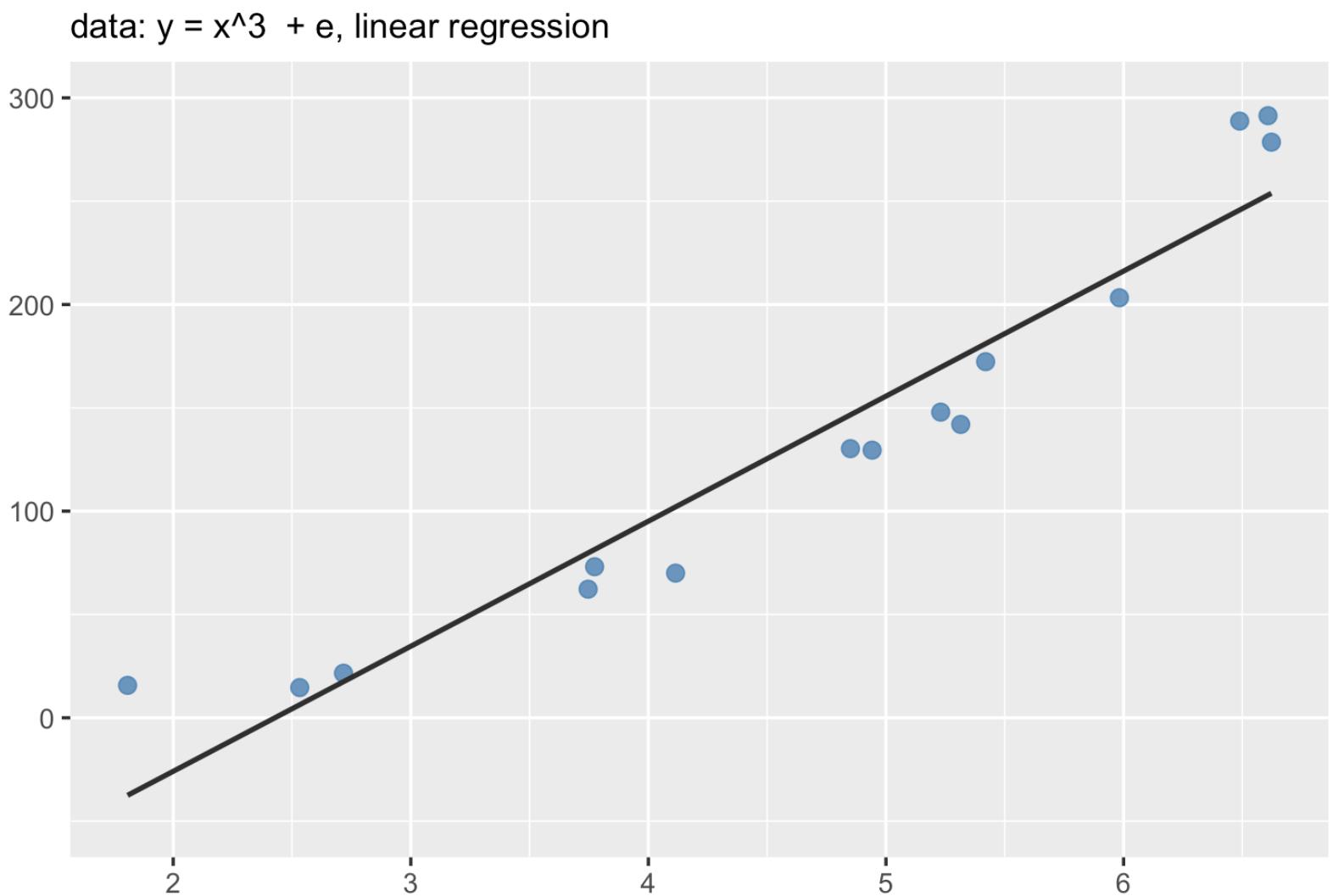
OVER- VS. UNDERFIT

- Problem in Machine Learning: Sufficiently complex algorithms can predict all training data **perfectly**
- But such an algorithm does not generalize to new data
- Essentially, we want the model to have a good fit to the data, but we also want it to not optimize on things that are specific to the training data set
- Let's try exemplify over vs. underfit with some simulated data!

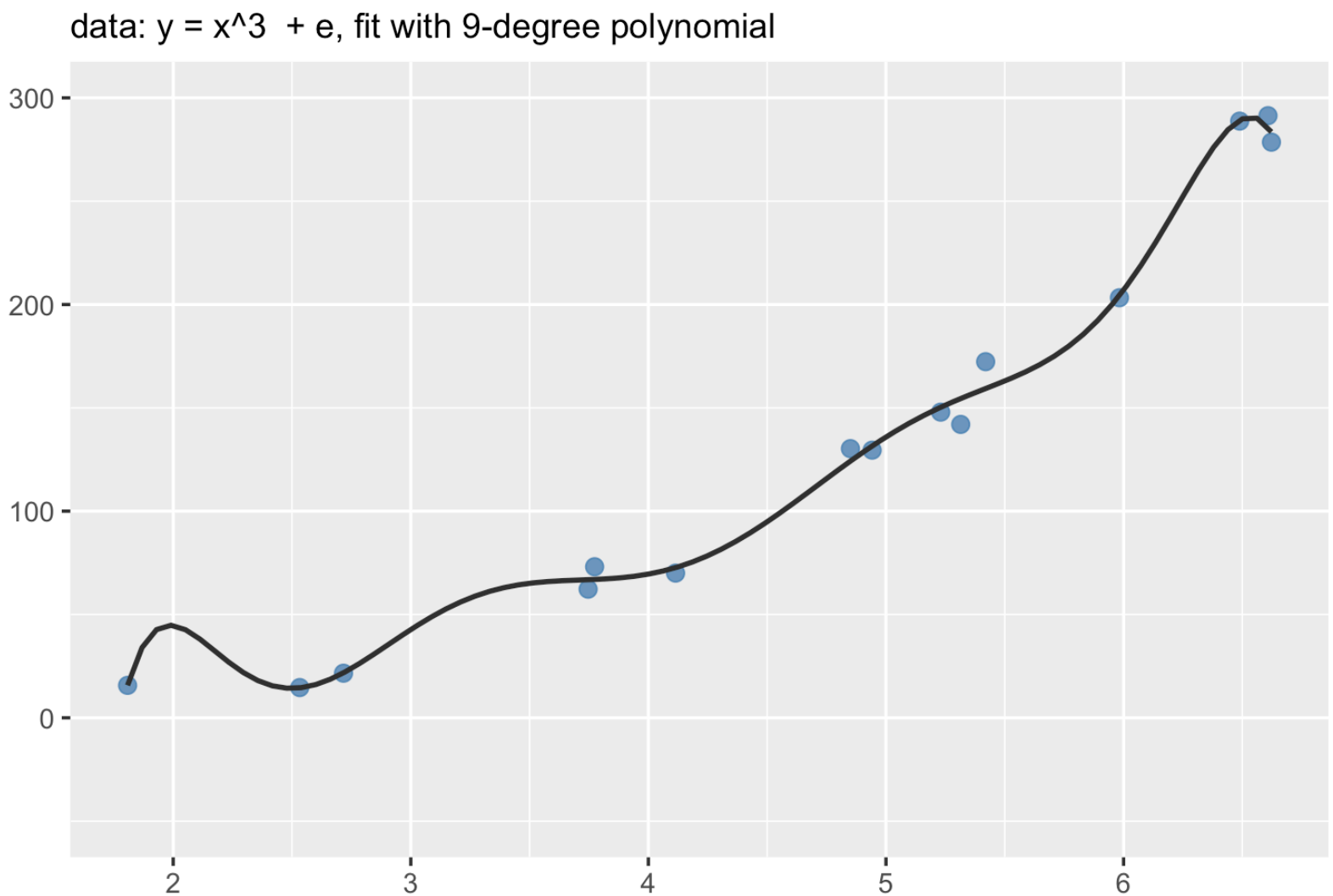
EXAMPLIFYING OVER- AND UNDERFIT



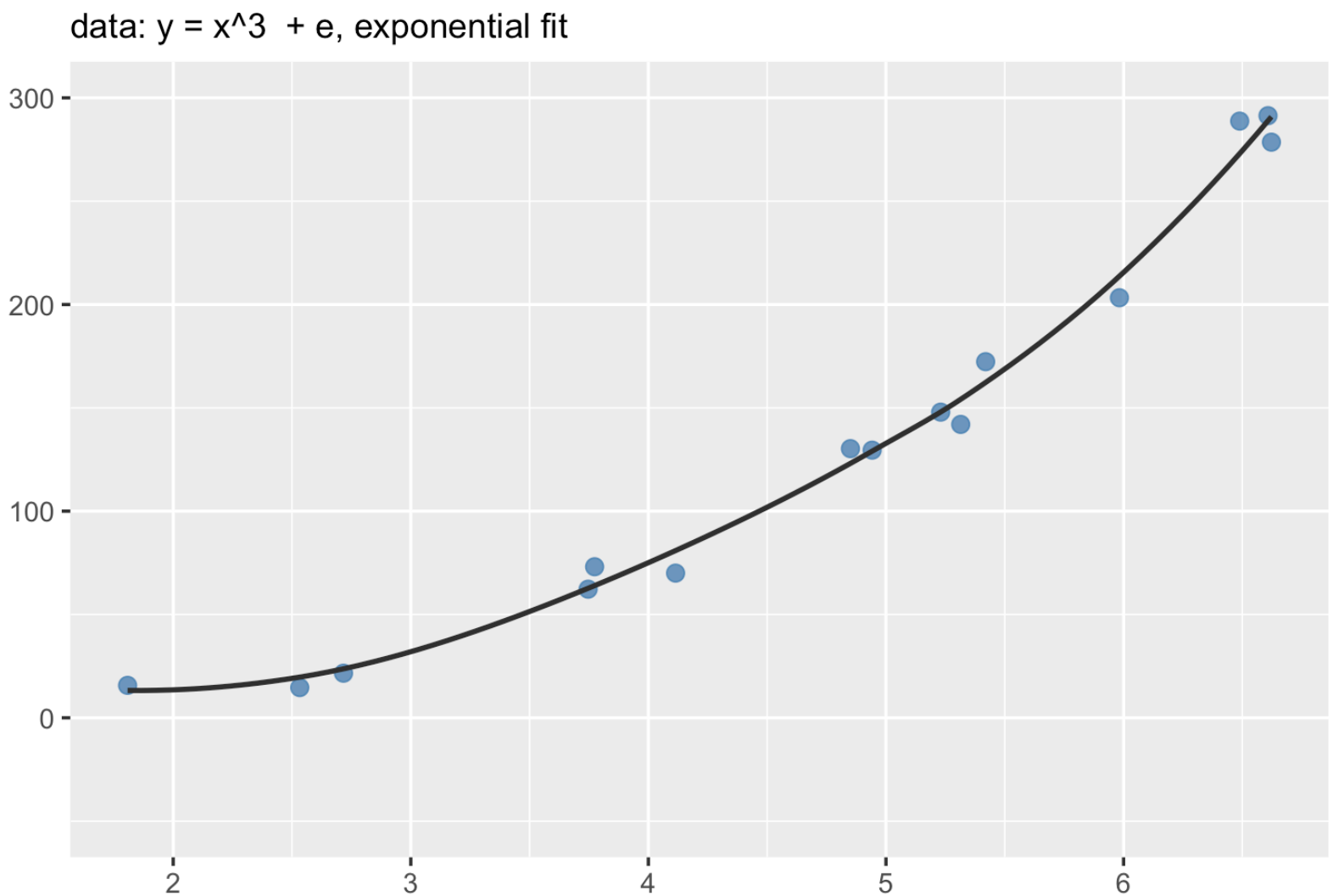
LINEAR FIT (UNDERFIT)



OVERFIT



GOOD FIT

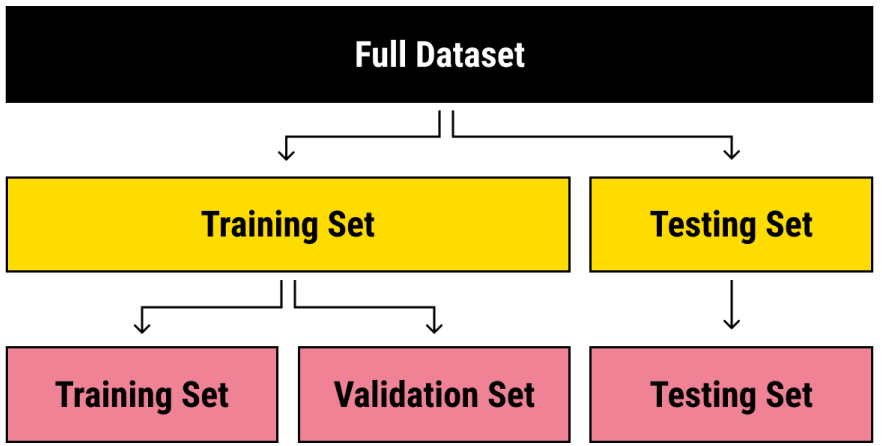


PREVENTING OVERFITTING

- Regularization during fitting process
  - ‘Punish’ complexity
  - Constrain flexibility
  - Removing noise
- Out-of-sample validation
  - To see whether a model generalizes to new data, simply test it on new data
  - This validation set clearly detects overfitting

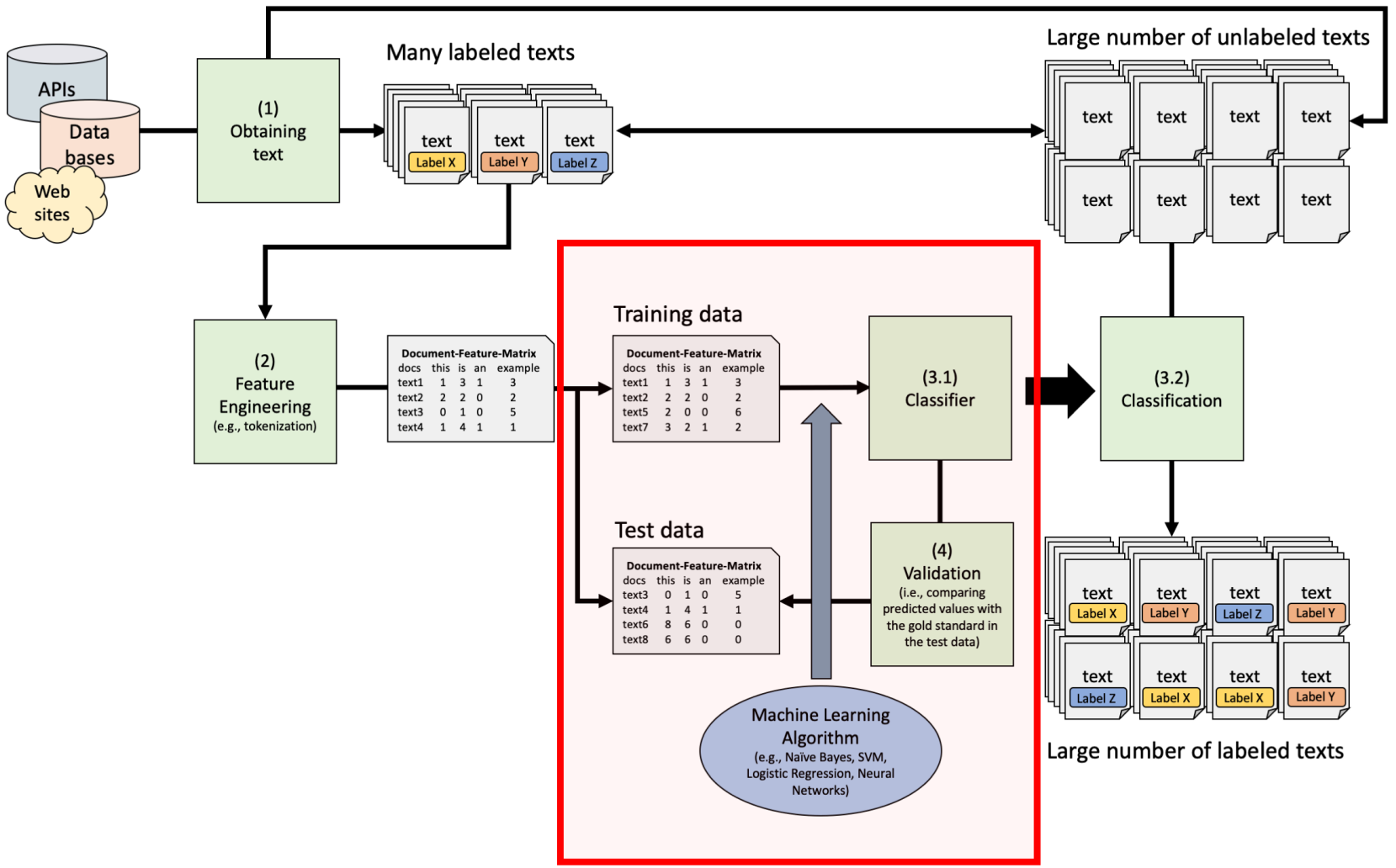
SOLUTION: TRAINING AND TESTING

- As models (almost) always overfit, performance on only training data is not a good indicator of the real quality of the classifier
- The standard solution is to split the labeled data into a training and test data sets: We train the algorithm on one part and then evaluate its performance on the held-out part



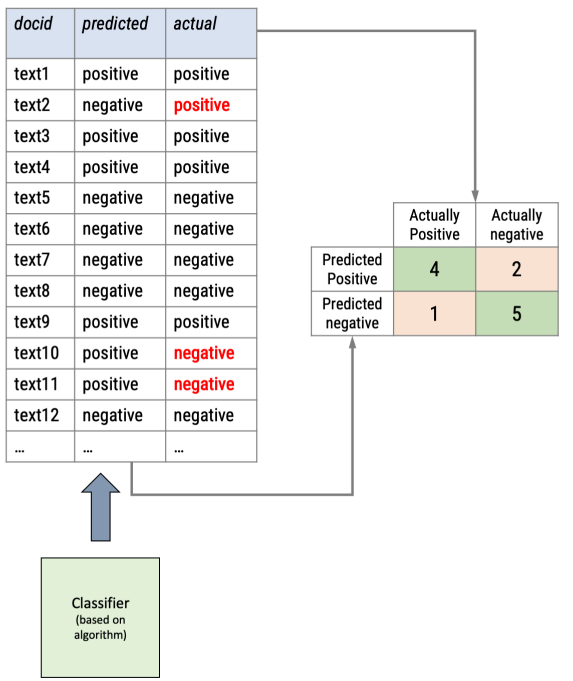
- In more elaborate scenarios, we distinguish in training, validation, and testing sets

INTEGRATING TESTING IN THE PIPELINE



TESTING = VALIDATION

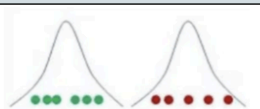
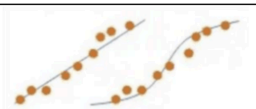
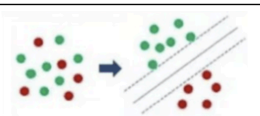
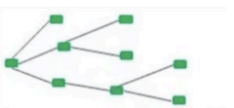
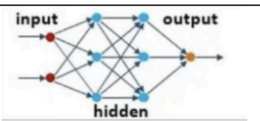
- Remember how we validated dictionary approaches?
  - We manually coded a small set of the text
  - Compared this gold standard to the dictionary result
- In supervised text classification, the procedure is similar:
  - We use the classifier, trained on the training data, to predict the outcome in the test data
  - Because the test data is only a subset of our labeled data, it also contains the true outcome
  - We compare the predicted with the actual outcome and compute the performance scores (Accuracy, Precision,…)



Text Classification with Artificial Neural Networks

Translating the Architecture of the Brain into Algorithmic Processing

OVERVIEW OF DIFFERENT ML ALGORITHMS

Algorithm	General Idea	Visualization	Strengths	Weaknesses
Naïve Bayes	A probabilistic classifier based on Bayes' theorem, assuming that features are independent given the class.		Fast to train, works well with small datasets, effective for text classification.	Assumes feature independence, which is often unrealistic; performance degrades when features are correlated.
Linear Regression Logistic Regression	Statistically model the relationship between a dependent and many independent variables		Simple to understand and interpret, computationally efficient, performs well with linearly separable data.	Poor performance on non-linear data, sensitive to outliers, limited flexibility without feature engineering.
Support Vector Machines	Finds a hyperplane that best separates classes by maximizing the margin between them.		Effective in high-dimensional spaces, works well with clear margins of separation, robust to overfitting in high-dimensional data.	Computationally expensive, especially with large datasets; not well-suited for non-linear problems without kernel tricks.
Decision Trees	A tree-like model of decisions and their possible consequences, where data is split based on feature values.		Easy to interpret and visualize, can handle both numerical and categorical data, no need for feature scaling.	Prone to overfitting, especially with deep trees; sensitive to small changes in data, which can cause instability.
Neural Networks	A network of nodes (neurons) organized in layers, where connections have weights adjusted through training to learn complex patterns.		Highly flexible, can model complex and non-linear relationships, effective for large datasets.	Requires large amounts of data and computational power, prone to overfitting, difficult to interpret.

→ In the following, we will focus primarily on neural networks as the most advanced algorithm in ML, but note that we could easily use other algorithms as well

DATA: PREDICTING DISCIPLINE FROM ABSTRACTS

- For the remainder of this lecture, I will exemplify different approaches to supervised text classification using a data set that contains the title and abstract of scientific articles and their discipline.

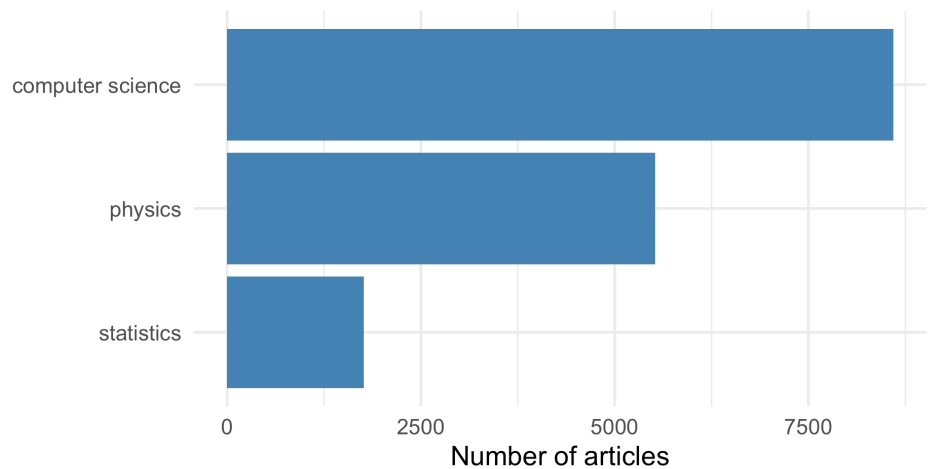
```
science_data <- read_csv("data/science.csv") |>
  filter(label != "biology" & label != "finance" & label != "mathematics")
science_data |>
  select(id, label, title, text)
```

```
# A tibble: 15,880 × 4
      id label            title                                                                text
   <dbl> <chr>            <chr>                                                                <chr>
 1     1 computer science Reconstructing Subject-Specific Effect Maps                          "Rec…
 2     2 computer science Rotation Invariance Neural Network                                   "Rot…
 3     5 computer science Comparative study of Discrete Wavelet Transforms and Wavelet Tensor Train decomposition… "Com…
 4     7 physics          On the rotation period and shape of the hyperbolic asteroid 1I/`Oumuamua (2017) U1 from… "On …
 5     8 physics          Adverse effects of polymer coating on heat transport at solid-liquid interface          "Adv…
 6     9 physics          SPH calculations of Mars-scale collisions: the role of the Equation of State, material … "SPH…
 7    11 computer science A global sensitivity analysis and reduced order models for hydraulically-fractured hori… "A g…
 8    12 physics          Role-separating ordering in social dilemmas controlled by topological frustration       "Rol…
 9    13 physics          Dynamics of exciton magnetic polarons in CdMnSe/CdMgSe quantum wells: the effect of sel… "Dyn…
10    14 computer science On Varieties of Ordered Automata                                    "On …
# ℹ 15,870 more rows
```

DATA: OVERVIEW OF DISCIPLINES

- The data contains articles from computer science, physics, and statistics
- Our goal is to find a neural network archtecture that can label abstracts with these disciplines sufficiently well

```
science_data |>
  group_by(label) |>
  tally() |>
  ggplot(aes(x = fct_reorder(label, n), y = n)) +
  geom_col(fill = "steelblue") +
  coord_flip() +
  theme_minimal(base_size = 20) +
  labs(x = "", y = "Number of articles")
```

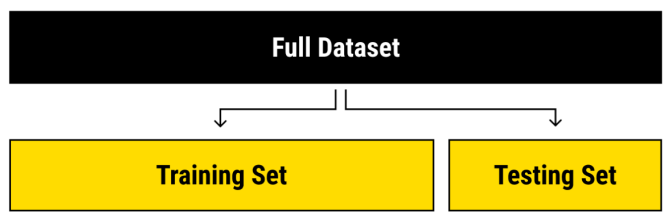


CREATING TRAINING AND TESTING DATA

- For the entire model fitting process, we are going to use the package `tidymodels`, which nicely intersects with the already known package `tidytext`
- Here, we can use the functions `initial_split` to split our data set. The functions `training` and `testing` create the actual data sets from the splits.

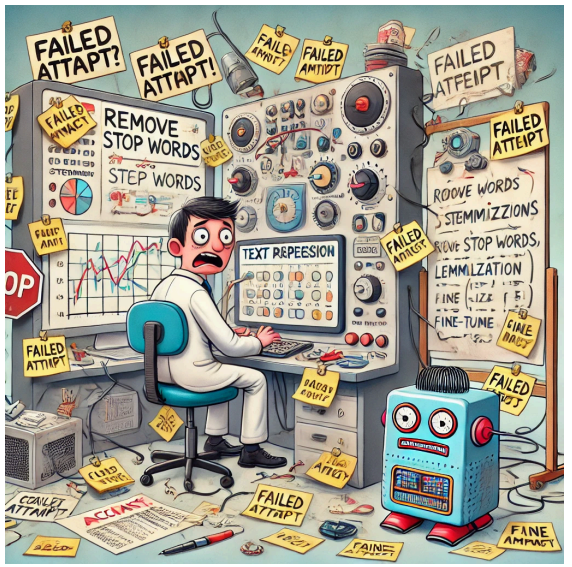
```
library(tidymodels)

# Set seed to insure replicability
set.seed(42)

# Create initial split proporations
split <- initial_split(science_data, prop = .90)

# Create training and test data
train_data <- training(split)
test_data <- testing(split)

# Check
tibble(dataset = c("training", "testing"),
       n_songs = c(nrow(train_data), nrow(test_data)))
```

```
# A tibble: 2 × 2
  dataset  n_songs
  <chr>      <int>
1 training   14292
2 testing     1588
```



FEATURE ENGINEERING

- Classic machine learning models require a numerical representation of text (e.g., document-feature matrix)
- They further need the outcome variable that they should predict
- All text-preprocessing steps (e.g., stopword removal, stemming, frequency trimming,etc.) may change the performance, but no clear rules on what works and what does not
- Only solution: Trial and error!



TEXT PREPROCESSING WITH TIDYTEXT

```r
library(tidytext)

# Text Preprocessing
dfm_train <- train_data |>
  unnest_tokens(word, text) |>                    # <-- Tokenization
  anti_join(stop_words) |>                        # <-- Remove stop words
  group_by(id, word) |>                           # <-- group by text and word
  summarize(n = n()) |>                           # <-- count word frequencies
  cast_dfm(document = id, term = word,  value = n) # <-- create DFM

# Check
dfm_train |>
  head()
```

```
Document-feature matrix of: 6 documents, 48,379 features (99.87% sparse) and 0 docvars.
    features
docs accuracy ad adni aims algorithm alterations alzheimer's amyloid analyses analyzing
   1        1  1    3    1         1           1           2       1        1         1
   2        0  0    0    0         0           0           0       0        0         0
   5        1  0    0    0         0           0           0       0        0         0
   7        0  0    0    0         0           0           0       0        0         0
   8        0  0    0    0         0           0           0       0        0         0
   9        0  0    0    0         0           0           0       0        0         0
[ reached max_nfeat ... 48,369 more features ]
```

ALTERNATIVE IN TIDYMODELS: CREATING A "RECIPE"

```r
library(textrecipes)

# Create recipe for text preprocessing
rec <- recipe(label ~ text, data = science_data) |>
  step_tokenize(text, options = list(strip_punct = T, strip_numeric = T)) |>  # <-- Tokenization
  step_stopwords(text, language = "en") |>                                    # <-- Remove stop words
  step_tf(all_predictors())                                                   # <-- Create DFM

# "Bake" (check) based on recipe to see text preprocessing
rec |>
  prep(train_data) |>
  bake(new_data=NULL)
```

```
# A tibble: 14,292 × 44,333
   label  tf_text__aster tf_text__b tf_text__c tf_text__catalogue tf_text__d tf_text__e tf_text__f tf_text__g tf_text__h
   <fct>           <int>      <int>      <int>              <int>      <int>      <int>      <int>      <int>      <int>
 1 stati…              0          0          0                  0          0          0          0          0          0
 2 physi…              0          0          0                  0          0          0          0          0          0
 3 physi…              0          0          0                  0          0          0          0          0          0
 4 compu…              0          0          0                  0          0          0          0          0          0
 5 compu…              0          0          0                  0          0          0          0          0          0
 6 compu…              0          0          0                  0          1          0          0          0          0
 7 compu…              0          0          0                  0          0          0          0          0          0
 8 physi…              0          0          0                  0          0          0          0          0          0
 9 physi…              0          0          0                  0          0          0          0          0          0
10 compu…              0          0          0                  0          0          0          0          0          0
# ℹ 14,282 more rows
# ℹ 44,323 more variables: tf_text__i <int>, tf_text__j <int>, tf_text__k <int>, tf_text__m <int>, tf_text__n <int>,
#   tf_text__p <int>, tf_text__q <int>, tf_text__r <int>, tf_text__s <int>, tf_text__svd <int>, tf_text__t <int>,
#   tf_text__u <int>, tf_text__v <int>, tf_text__x <int>, tf_text__y <int>, tf_text__z <int>, tf_text_0.0001s <int>,
#   tf_text_0.031mj <int>, tf_text_0.05dex <int>, tf_text_0.12v <int>, tf_text_0.18um <int>, tf_text_0.1c <int>,
#   tf_text_0.1dex <int>, tf_text_0.254r <int>, tf_text_0.2c <int>, tf_text_0.2db <int>, tf_text_0.2l <int>,
#   tf_text_0.2r_ <int>, tf_text_0.3a <int>, tf_text_0.3t_ <int>, tf_text_0.4gyr <int>, tf_text_0.4k <int>, …
```

WORKFLOW IN TIDYMODELS

- The collection `tidymodels` contains a variety of packages that facilitates and streamlines machine learning in R
- The basic procedure is the following:
  1. Create a **recipe** (a formula and all pre-processing steps)
  2. **Bake** training and testing data using the **recipe** (not explicitly necesssary)
  3. Create a **model function** (depending on what type of algorithm should be used)
  4. Bind all together using a **workflow**
  5. **Fit** the entire **workflow** and evaluate performance

SETTING UP A RECIPE FOR OUR EXAMPLE

```
# Load specific support library
library(textrecipes)

# Create recipe
rec <- recipe(label ~ text, data = science_data)                    # <-- predict binary_genre by text
```

SETTING UP A RECIPE FOR OUR EXAMPLE

```
# Load specific support library
library(textrecipes)

# Create recipe
rec <- recipe(label ~ text, data = science_data) |>              # <-- predict binary_genre by text
  step_tokenize(text, options = list(strip_punct = T,            # <-- tokenize, remove punctuation
                                     strip_numeric = T))         # <-- remove numbers
```

SETTING UP A RECIPE FOR OUR EXAMPLE

```
# Load specific support library
library(textrecipes)

# Create recipe
rec <- recipe(label ~ text, data = science_data) |>              # <-- predict binary_genre by text
  step_tokenize(text, options = list(strip_punct = T,            # <-- tokenize, remove punctuation
                                     strip_numeric = T)) |>      # <-- remove numbers
  step_stopwords(text, language = "en") |>                       # <-- remove stopwords
  step_tokenfilter(text, min_times = 20, max_tokens = 1000)      # <-- filter out rare words and use only top 1000
```

SETTING UP A RECIPE FOR OUR EXAMPLE

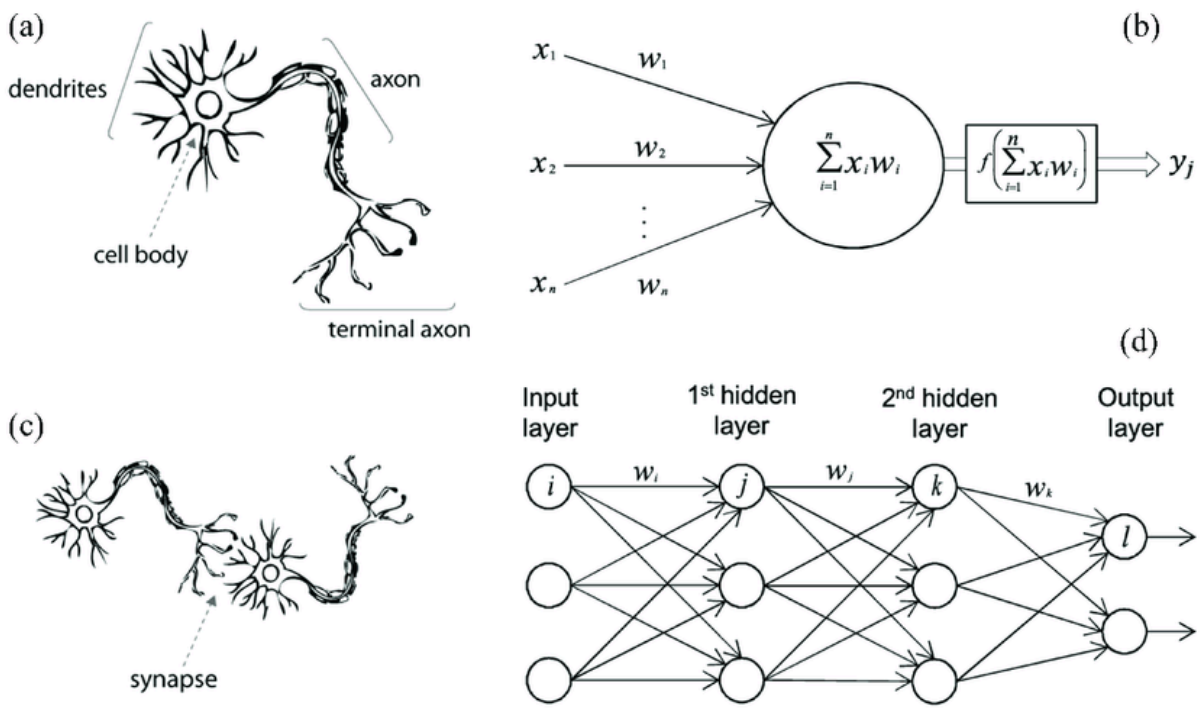
```
# Load specific support library
library(textrecipes)

# Create recipe
rec <- recipe(label ~ text, data = science_data) |>              # <-- predict binary_genre by text
  step_tokenize(text, options = list(strip_punct = T,            # <-- tokenize, remove punctuation
                                     strip_numeric = T)) |>      # <-- remove numbers
  step_stopwords(text, language = "en") |>                       # <-- remove stopwords
  step_tokenfilter(text, min_times = 20, max_tokens = 1000) |>   # <-- filter out rare words and use only top 1000
  step_tf(all_predictors())                                      # <-- create document-feature matrix
```

SETTING UP A RECIPE FOR OUR EXAMPLE

```
# Load specific support library
library(textrecipes)

# Create recipe
rec <- recipe(label ~ text, data = science_data) |>              # <-- predict binary_genre by text
  step_tokenize(text, options = list(strip_punct = T,            # <-- tokenize, remove punctuation
                                     strip_numeric = T)) |>      # <-- remove numbers
  step_stopwords(text, language = "en") |>                       # <-- remove stopwords
  step_tokenfilter(text, min_times = 20, max_tokens = 1000) |>   # <-- filter out rare words and use only top 1000
  step_tf(all_predictors())                                      # <-- create document-feature matrix

# Small adaption to the recipe (for SVM and neural networks)
rec_norm <- rec |>
  step_normalize(all_predictors())
```

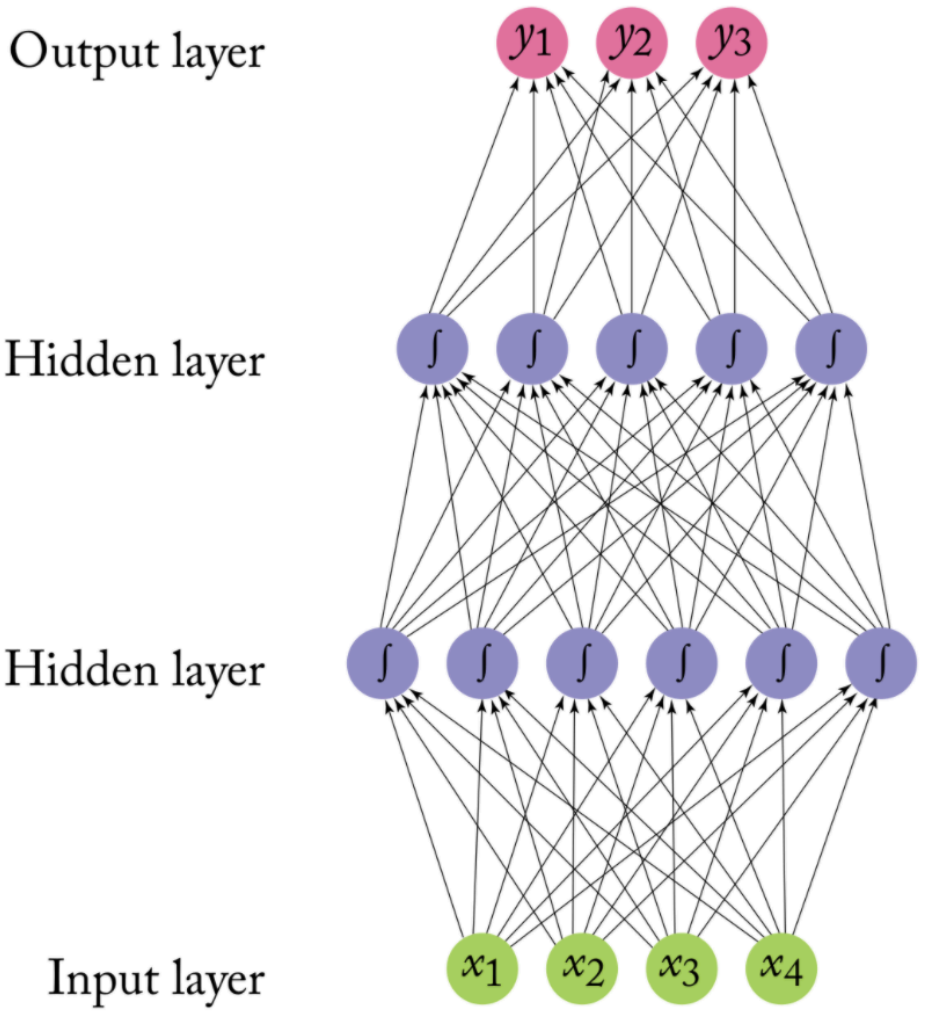
THEORETICAL BACKGROUND

- An artificial neural network models the relationship between a set of input signals and an output signal using a model derived from our understanding of the human brain
- Like a brain uses a network of interconnected cells called “neurons” (a) to provide fast learning capabilities, a neural network uses a network of artificial neurons (b) to solves learning tasks



Source: Arthur Arnx/Medium

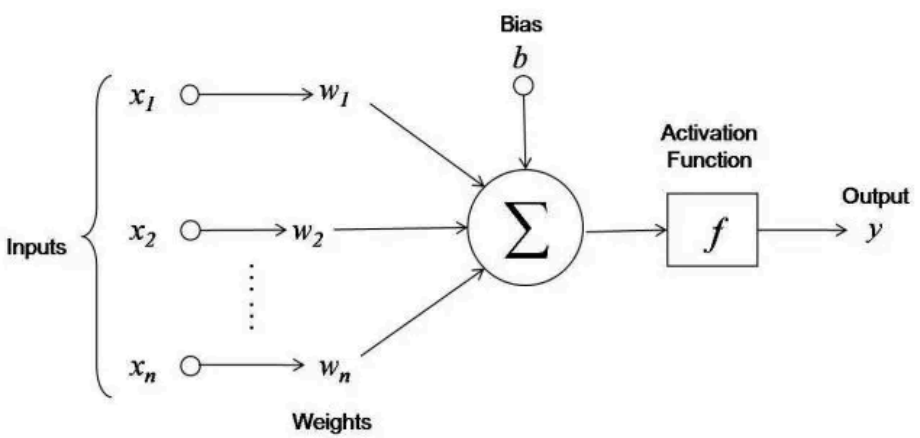
HOW DOES A NEURAL NETWORK WORK?



- The operation of an artificial neural network is straightforward:
  - One enters variables as inputs (e.g., features of a text)
  - And after some calculations via different neurons, an output is returned (e.g. the word “politics”)
- Neurons are stacked on top of one another and a neuron of colum `n` can only be connected to inputs from column `n-1` and provide outputs to neurons in column `n+1`
- In other words, input data are passed through layered transformations until an output is reached

THE NEURON AS GENERALIZED LINEAR MODEL

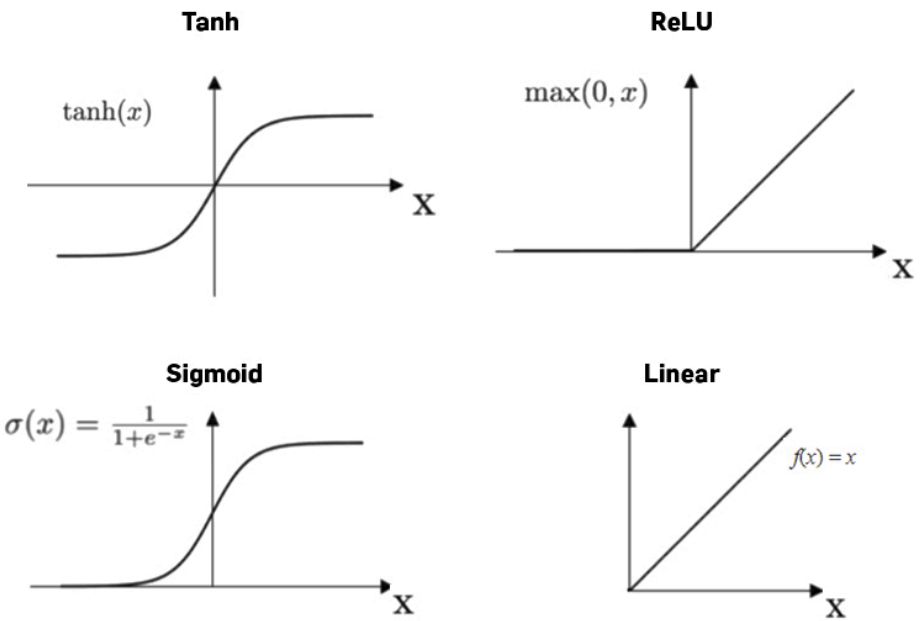
- First, the value of each input neuron is multiplied by so-called “weight” (`w1`, `w2`, `w3`), which could be regarded as the strength of connection between two neurons
- Second, the neuron adds up the values of every input neuron from the previous column it is connected to (here `x1`, `x2`, and `x3`)
- Third, a bias value may be added (e.g., to regularize the network)
- After all those summations, the neuron finally applies a function called “activation function” to the obtained value



Source: Arthur Arnx/Medium

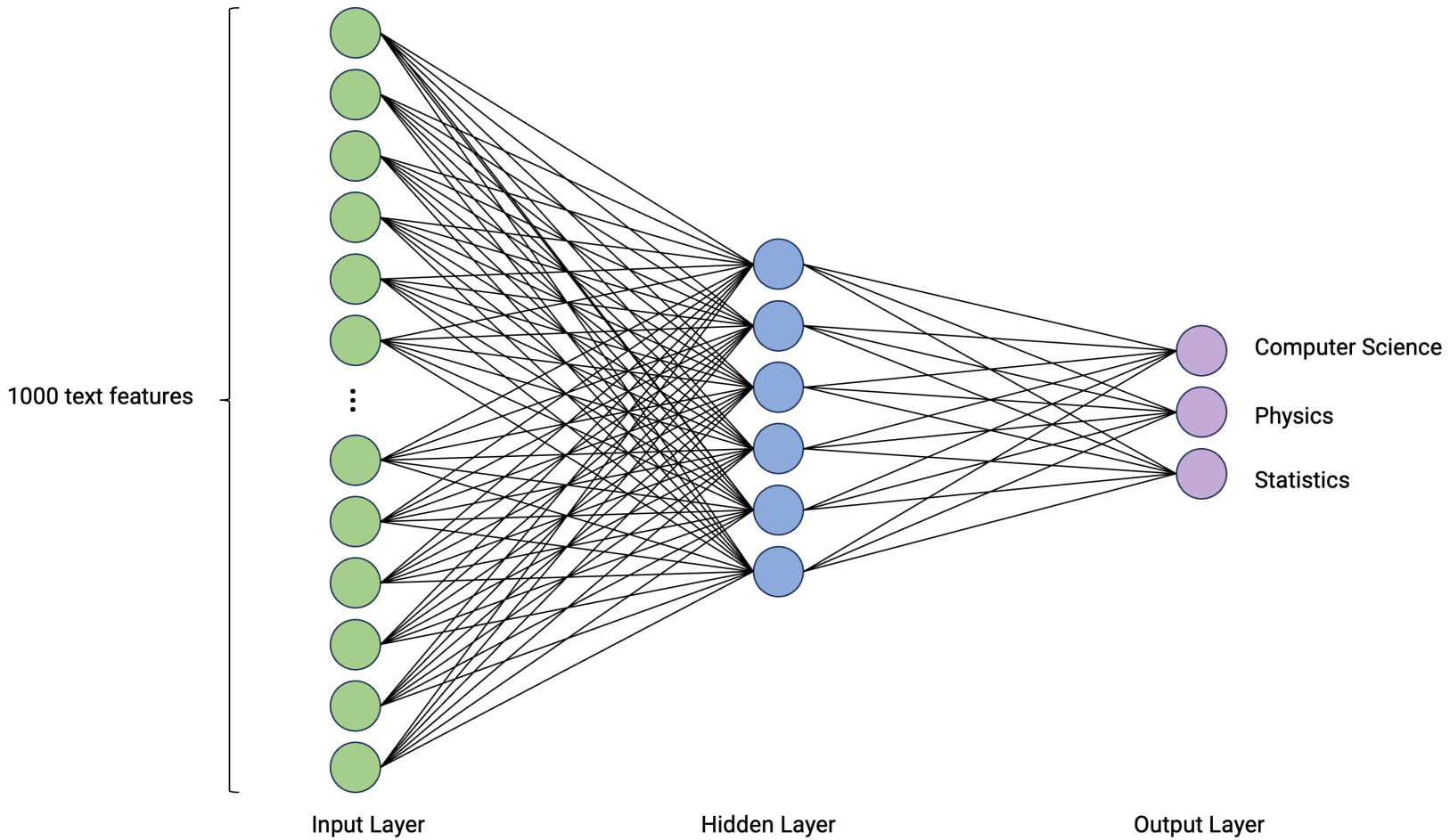
THE ACTIVATION FUNCTION

- The activation function serves to turn the total value calculated to a number between 0 and 1
- A threshold then defines at what value the function should “fire” the output to the next neuron (of course this can be probabilistic)
- We can choose from different activation functions; which works best is sometimes hard to tell

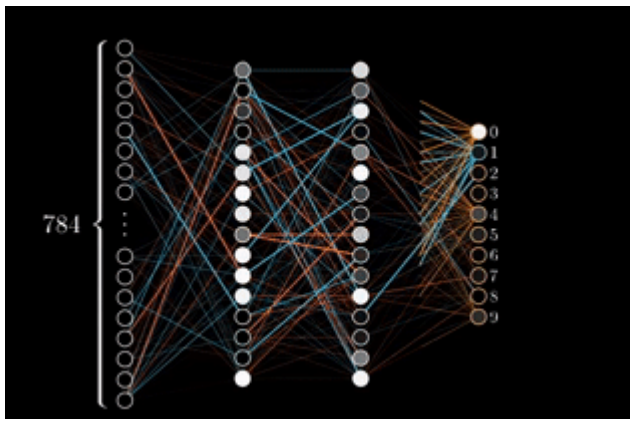


Source: AI Wiki

A MULTILAYER PERCEPTRON FOR OUR EXAMPLE



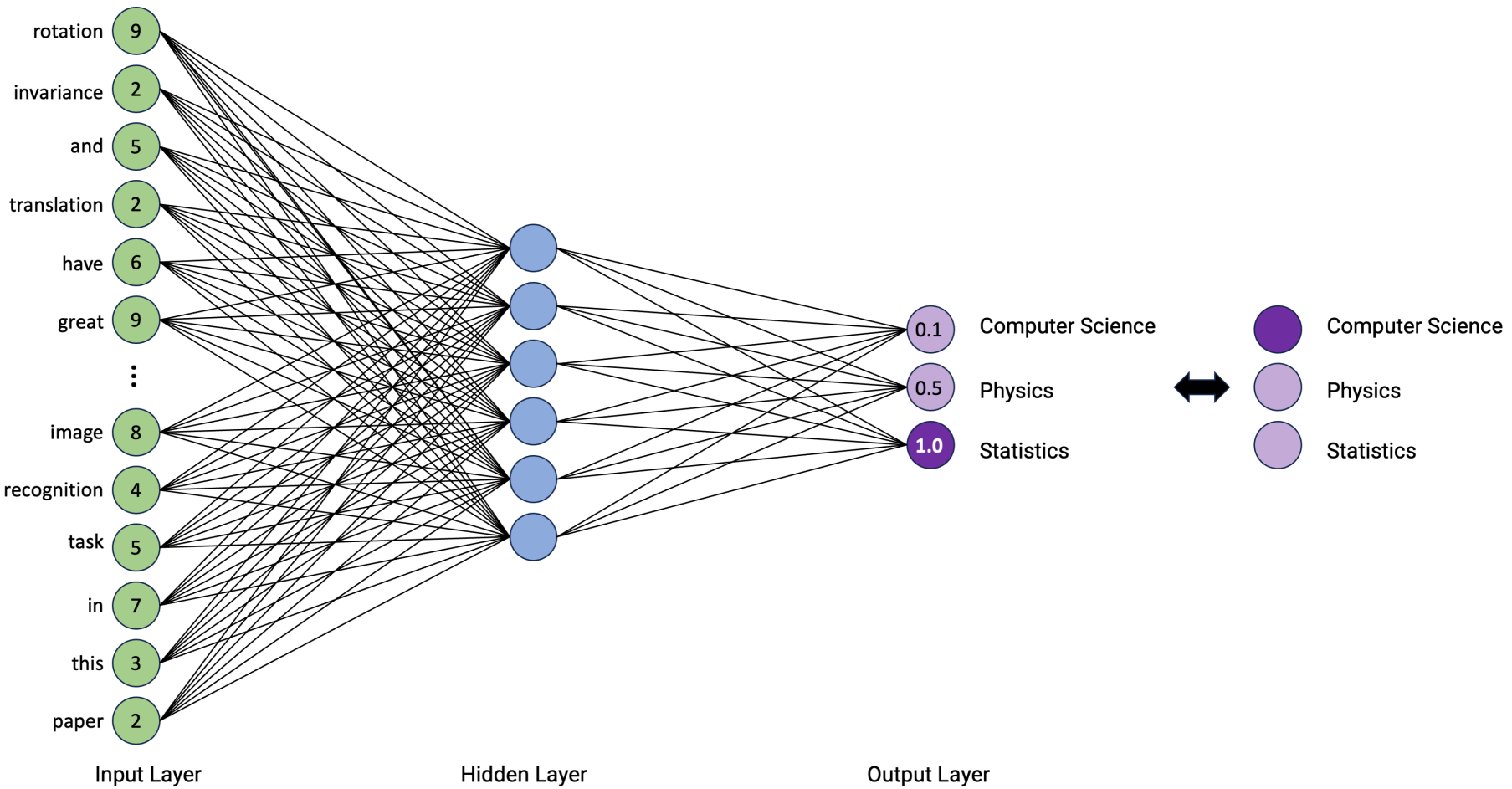
HOW THE NEURAL NETWORK LEARNS



- In a first try, the neural network randomly sets weights and thus can't get the right output (except with luck)
- If the random choice was a good one, actual parameters are kept and the next input is given. If the obtained output doesn't match the desired output, the weights are changed
- To determine which weight is better to modify, a neural network uses **backpropagation**, which consists of "going back" on the neural network and inspect every connection to check how the output would behave according to a change on the weight
- The **learning rate** thereby determines the speed a neural network will learn, i.e., how it will modify a weight (e.g., little by little or by bigger steps).
- Learning rate and number of learning cycles (so-called epochs) have to be set manually upfront!

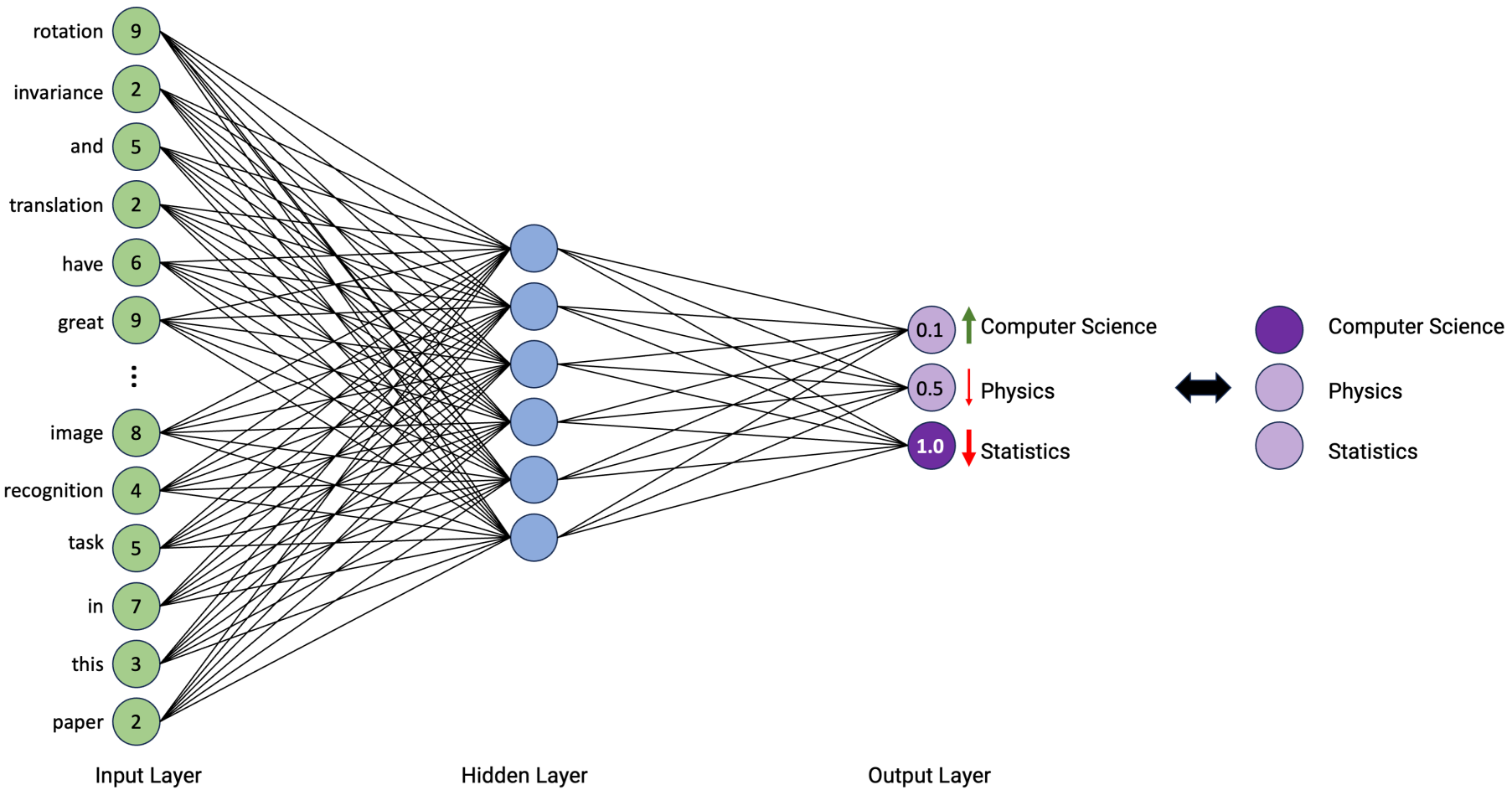
BACKPROPAGATION IN DETAIL: RANDOM INITIALIZATION

Rotation Invariance Neural Network
Rotation invariance and translation invariance have great values in image recognition tasks. In this paper, we bring a new architecture in convolutional neural network (CNN) named cyclic convolutional layer ...



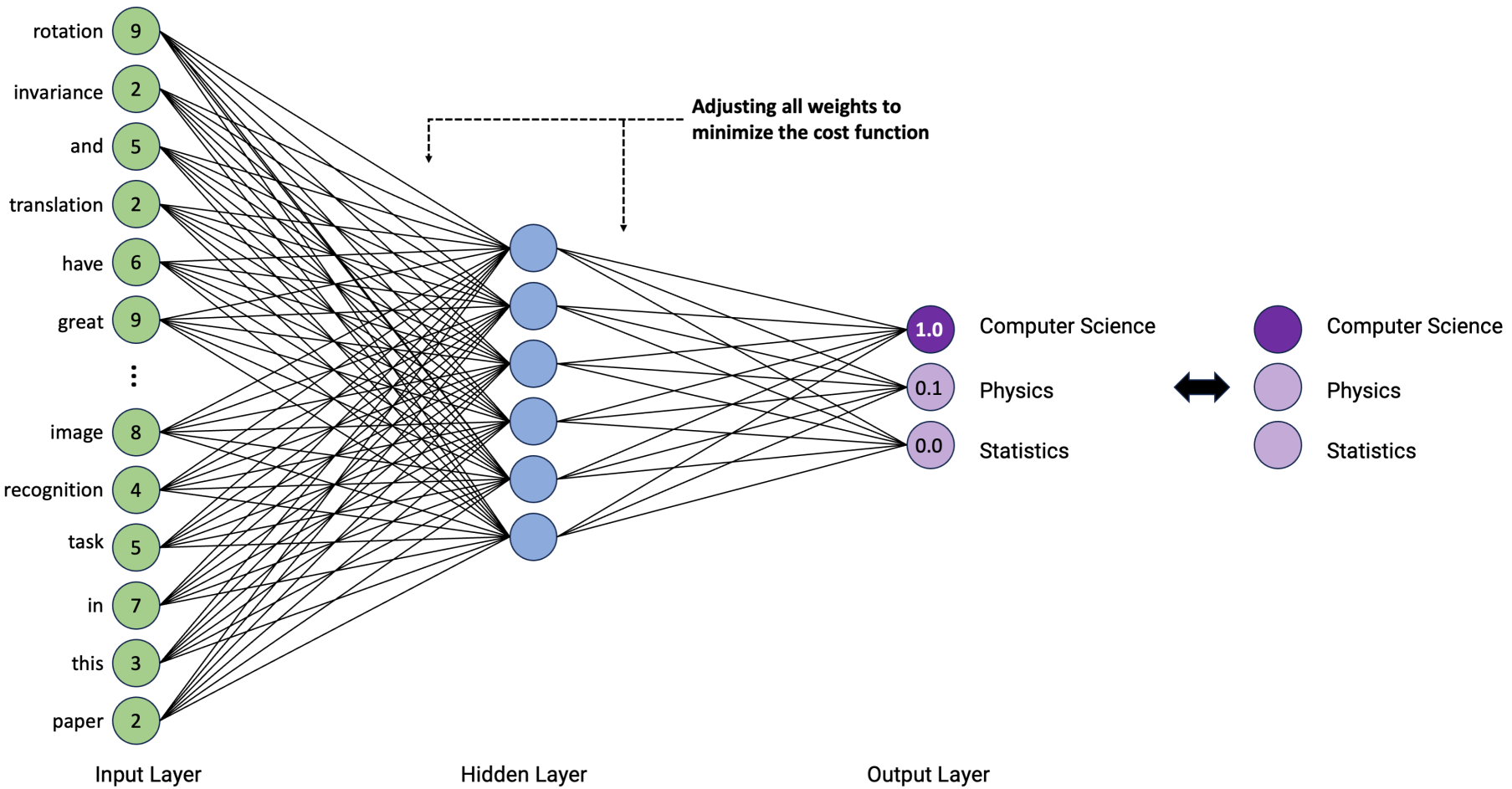
BACKPROPAGATION IN DETAIL: COSTS FUNCTION

Rotation Invariance Neural Network
Rotation invariance and translation invariance have great values in image recognition tasks. In this paper, we bring a new architecture in convolutional neural network (CNN) named cyclic convolutional layer ...



BACKPROPAGATION IN DETAIL: ADJUSTING WEIGHTS

Rotation Invariance Neural Network
Rotation invariance and translation invariance have great values in image recognition tasks. In this paper, we bring a new architecture in convolutional neural network (CNN) named cyclic convolutional layer ...

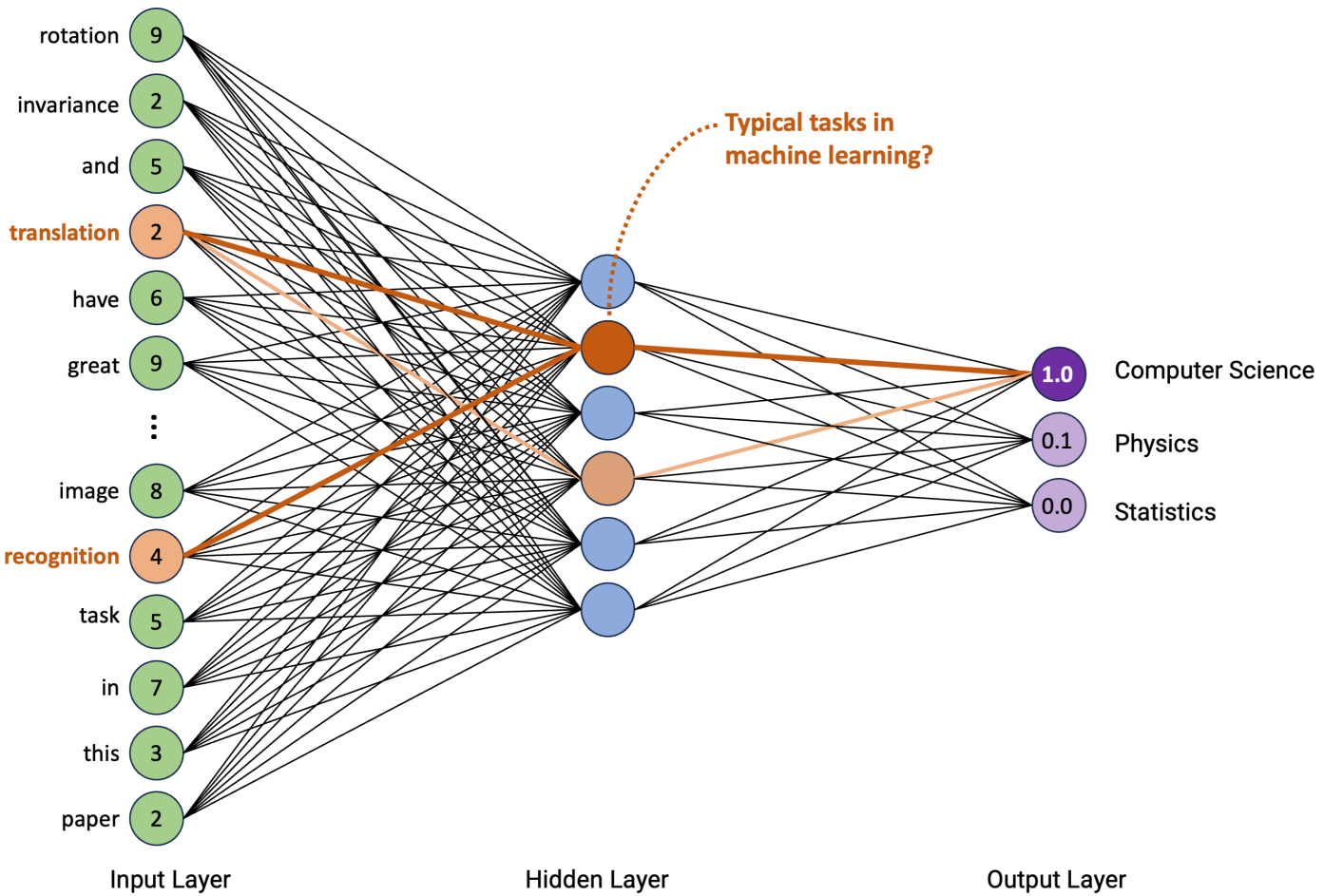


WHAT DID THE NEURAL NETWORK LEARN?

- It is hard to imagine how the network has learned that a certain combination of words corresponds to a certain label.
- In fact, we can only speculate that it might capture certain meaning by co-occurence of words, e.g., that certain words are representing machine learning and machine learning, in turn, is most likely to be within “computer science”

WHAT A NEURAL NETWORK MIGHT HAVE LEARNED…

Rotation Invariance Neural Network
Rotation invariance and translation invariance have great values in image recognition tasks. In this paper, we bring a new architecture in convolutional neural network (CNN) named cyclic convolutional layer …



WHAT A NEURAL NETWORK MIGHT HAVE LEARNED…

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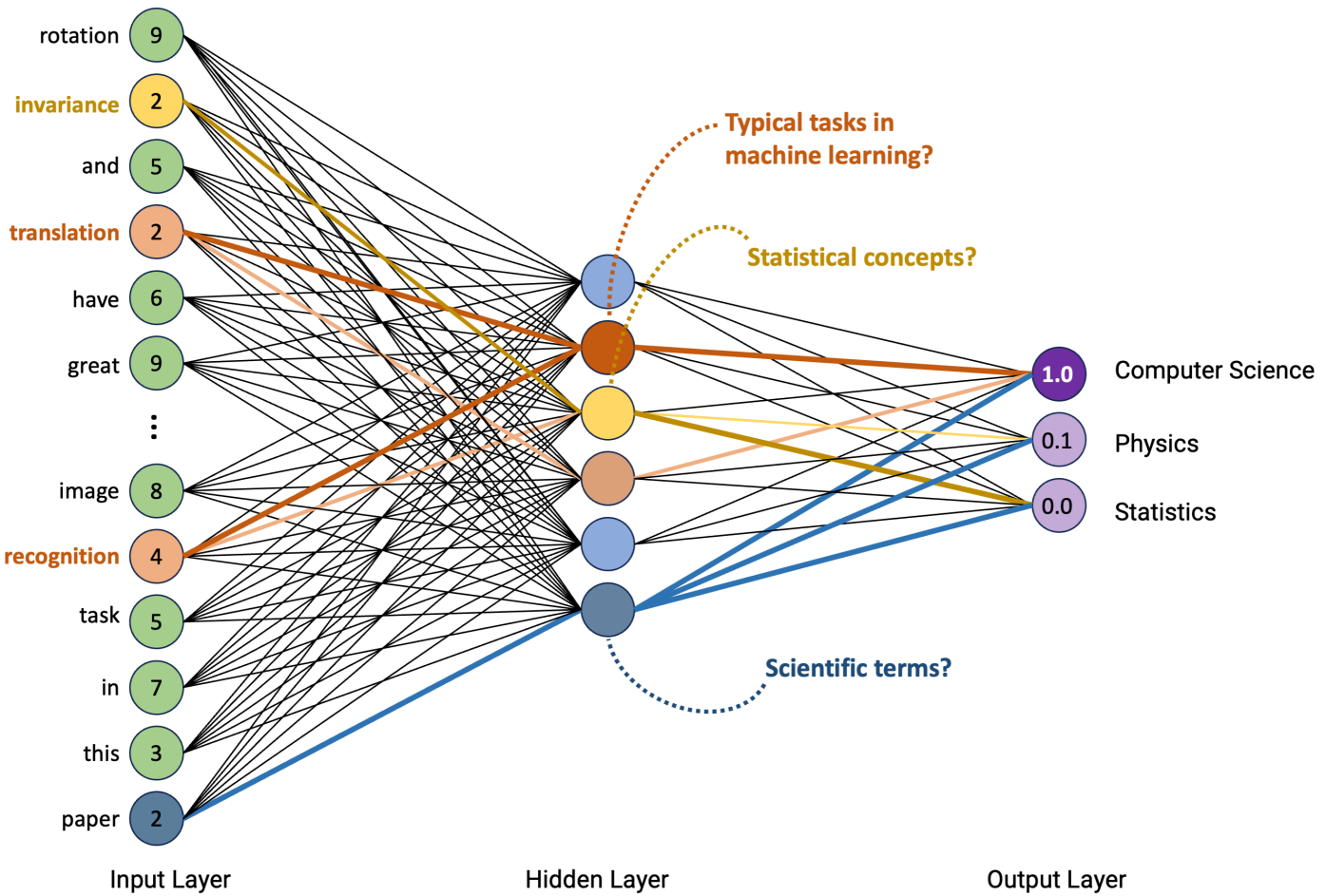

FITTING AN ARTIFICAL NEURAL NETWORK

```
# For replication purposes
set.seed(42)

# Specify multilayer perceptron
nnet_spec <-
  mlp(epochs = 400,          # <- times that algorithm will work through train set
      hidden_units = c(6),   # <- nodes in hidden units
      penalty = 0.01,        # <- regularization
      learn_rate = 0.2) |>   # <- shrinkage
  set_engine("brulee") |>    # <- engine = R package
  set_mode("classification")

# Create workflow
ann_workflow <- workflow() |>
  add_recipe(rec_norm) |>    # Use updated recipe with normalization
  add_model(nnet_spec)
```

FITTING AN ARTIFICAL NEURAL NETWORK

```
# For replication purposes
set.seed(42)

# Specify multilayer perceptron
nnet_spec <-
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  set_engine("brulee") |>    # <- engine = R package
  set_mode("classification")

# Create workflow
ann_workflow <- workflow() |>
  add_recipe(rec_norm) |>    # Use updated recipe with normalization
  add_model(nnet_spec)

# Fit model
m_ann <- fit(ann_workflow, train_data)
```

PREDICTING LABELS IN THE TESTING DATA

- We then use the resulting classifier (the neural network) to classify the test data and compare it with the actual labels

```
# Predict outcome in test data
predict_ann <- predict(m_ann, new_data = test_data) %>%
  bind_cols(test_data) |>
  mutate(truth = factor(label)) |>
  select(id, predicted = .pred_class, truth, title)

# Check
predict_ann |>
 head(n = 4)
```

```
# A tibble: 4 × 4
     id predicted        truth            title
  <dbl> <fct>            <fct>            <chr>
1    31 computer science computer science mixup: Beyond Empirical Risk Minimiza…
2    35 computer science computer science Deep Neural Network Optimized to Resi…
3    48 computer science computer science Wehrl Entropy Based Quantification of…
4    55 computer science computer science An Effective Framework for Constructi…
```

- In `tidymodels`, we have to define a set of measures that we want to compute based on the predictions in the test set.

```
# Define a set of performance scores to be computed
class_metrics <- metric_set(accuracy, precision, recall, f_meas)
```

VALIDATION

- We then can inspect the confusion matrix
- We see here that it does get a lot of articles right, but there are also some false positives and false negatives

```
# Confusion matrix
predict_ann |>
  conf_mat(truth = truth, estimate = predicted)
```

```
                 Truth
Prediction         computer science physics statistics
  computer science              811      30        105
  physics                        22     539          4
  statistics                     17       1         59
```

- Based on the performance scores, we see that it actually doesn't perform bad at all

```
# Performance score
predict_ann |>
  class_metrics(truth = truth, estimate = predicted)
```

```
# A tibble: 4 × 3
  .metric   .estimator .estimate
  <chr>     <chr>          <dbl>
1 accuracy  multiclass     0.887
2 precision macro          0.859
3 recall    macro          0.750
4 f_meas    macro          0.778
```

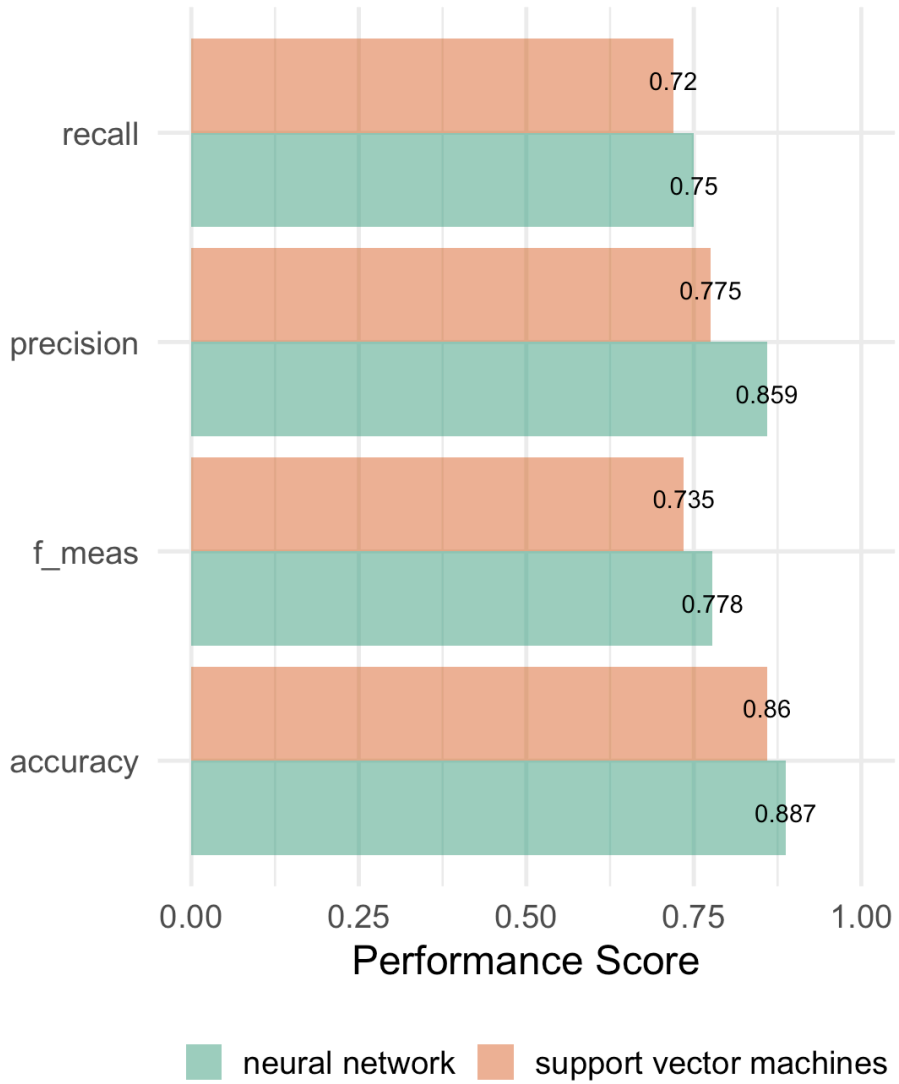
FITTING A DIFFERENT MODEL (E.G., SVM)

- With `tidymodels`, we can very easily use a different algorithm.
- Because we already set up a recipe that works with Support Vector Machines, the only thing we have to do is update the workflow and add the new model

```
library(LiblineaR)

# Updating the workflow
svm_workflow <- workflow() |>
  add_recipe(rec_norm) |>                          # <-- Recipe remains the same!
  add_model(svm_linear(mode = "classification",    # <-- We just add a new model (e.g Support Vector Machines)
                       engine = "LiblineaR"))

# Fitting the SVM model
m_svm <- fit(svm_workflow, data = train_data)
```

COMPARISON OF THE PREVIOUS APPROACHES

```r
# Predict test data
predict_svm <- predict(m_svm, new_data=test_data) |>
  bind_cols(test_data) |>
  mutate(truth = factor(label)) |>
  select(id, predicted = .pred_class, truth, title)

# Combine predict data from SVM and neural network
bind_rows(
  # Compute class_metrics for SVM
  predict_svm |>
    class_metrics(truth=truth, estimate=predicted) |
    mutate(algorithm = "support vector machines"),
  # Compute class_metrics for NN
  predict_ann |>
    class_metrics(truth=truth, estimate=predicted) |
    mutate(algorithm = "neural network")) |>
  # Plot comparison
  ggplot(aes(x = .metric, y = .estimate,
             fill = algorithm)) +
  geom_col(position=position_dodge(), alpha=.5) +
  geom_text(aes(label = round(.estimate, 3)),
            position = position_dodge(width=1)) +
  ylim(0, 1) +
  coord_flip() +
  scale_fill_brewer(palette = "Dark2") +
  theme_minimal(base_size = 18) +
  theme(legend.position = "bottom") +
  labs(y = "Performance Score", x = "", fill = "")
```



Break (5 Minutes)

Word-Embeddings

More Complex Text Representations

REMBER: THE INITIAL PROBLEM OF TEXT ANALYSIS

- Computers don't read text, they only can deal with numbers
- For this reason, so far, we tokenized our texts (e.g., in words) and summarized their frequency across texts to create a document-feature matrix within the **bag-of-words model**

Classic Document-Feature Matrix

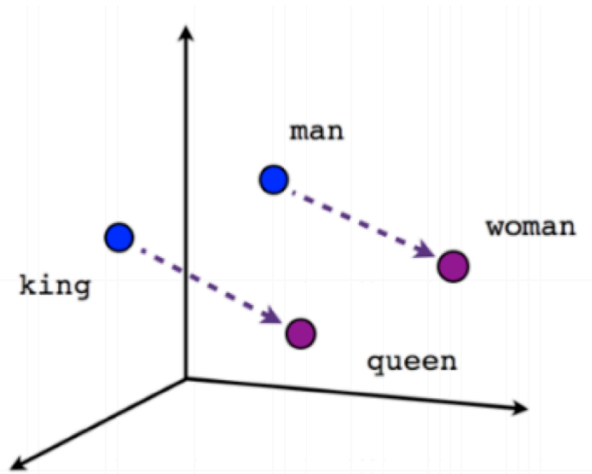
docid	*be*	*is*	*not*	*or*	*question*	*that*	*to*	...
text1	2	1	1	1	1	1	2	...
text2	1	0	0	0	0	0	0	...

- Such a text representation has some issues:
  - Treats words as equally important (→ requires removal of noise, stopwords…)
  - Ignores word order and context
  - Results in a sparse matrix (→ computationally expensive)

ALTERNATIVE: MAP WORDS INTO A VECTOR SPACE

Word-Embedding Matrix:

dimensions	*king*	*man*	*queen*	*women*
1 *(royalty)*	0.99	0.20	0.99	0.30
2 *(masculinity)*	0.99	0.99	0.05	0.05
3 *(feminity)*	0.05	0.05	0.99	0.99
4 *(...)*	0.45	0.82	0.39	0.79



Allows for mathematical operations:

king		*man*		*women*		*results*	≈	*queen*
0.99	−	0.20	+	0.30	=	1.09	≈	0.99
0.99	−	0.99	+	0.05	=	0.05	≈	0.05
0.05	−	0.05	+	0.99	=	0.99	≈	0.99
0.45	−	0.82	+	0.79	=	0.42	≈	0.40

→ Most similar vector in the data set

(STATIC) WORD EMBEDDINGS

- Word embeddings are a “learned” type of **word representation** that allows words with similar meaning to have a similar representation via a *k*-dimensional vector space
- The first core idea behind word embeddings is that the meaning of a word can be expressed using a relatively small embedding vector, generally consisting of around 300 numbers which can be interpreted as dimensions of meaning
- The second core idea is that these embedding vectors can be derived by scanning the context of each word in millions and millions of documents.
- This means that words that are used in similar ways in the training data result in similar representations, thereby capturing their similar meaning.

HOW DO WE GET THESE “VALUES” FOR EACH WORD?

All word embedding methods learn a real-valued vector representation for a predefined fixed-sized vocabulary from a corpus of text:

1. Via an embedding layer in a neural network designed for a particular downstream task
2. Learning word embeddings using a shallow neural network and context windows (e.g., **word2vec**)
3. Learning word embeddings by aggregating global word-word co-occurrence matrix (e.g., GloVe)

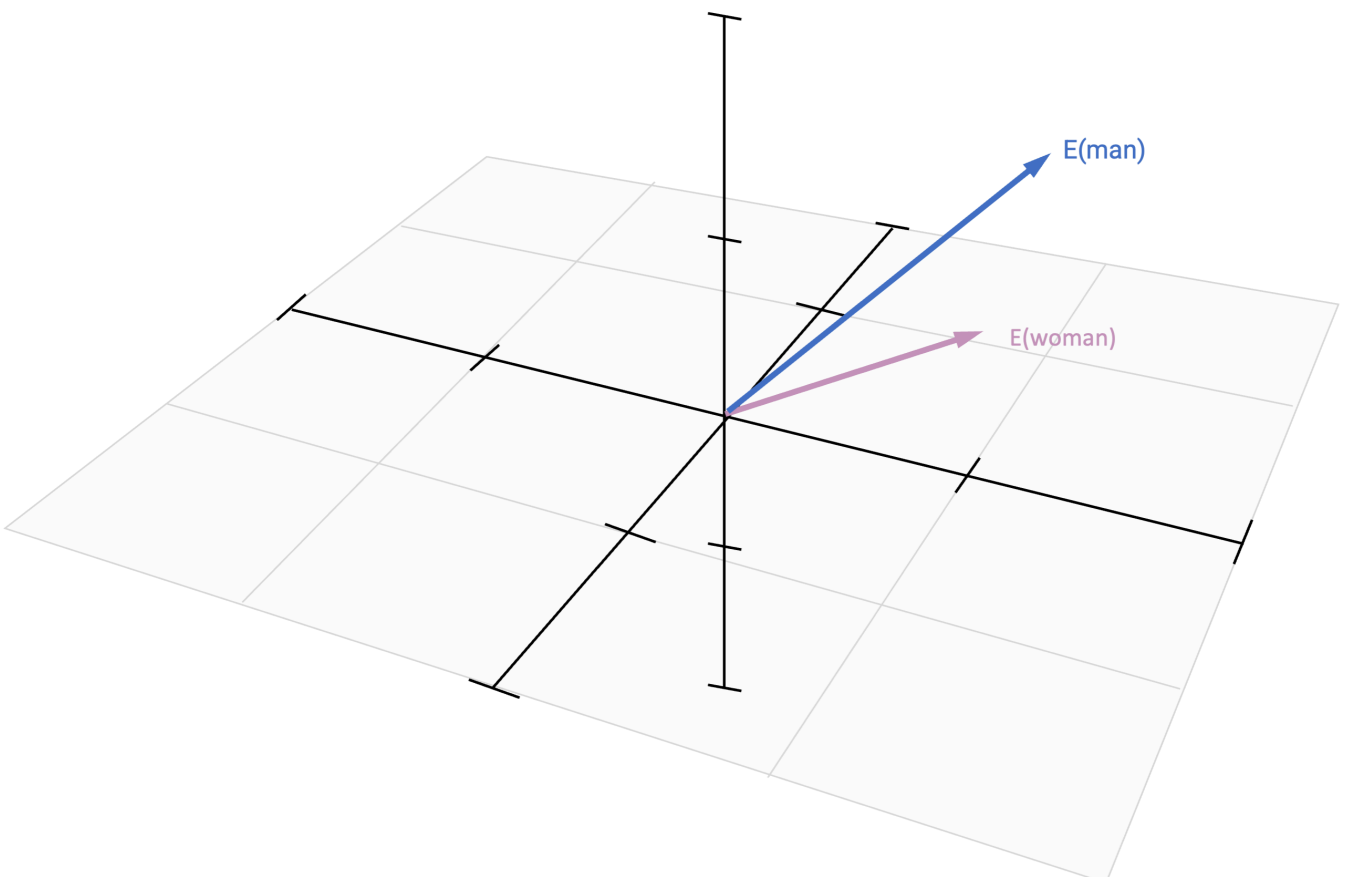
PRE-TRAINED WORD EMBEDDINGS: GLOVE

- GloVe captures global statistical information from a text corpus by looking at word co-occurrences across the entire corpus, not just in local contexts (like neighboring words):

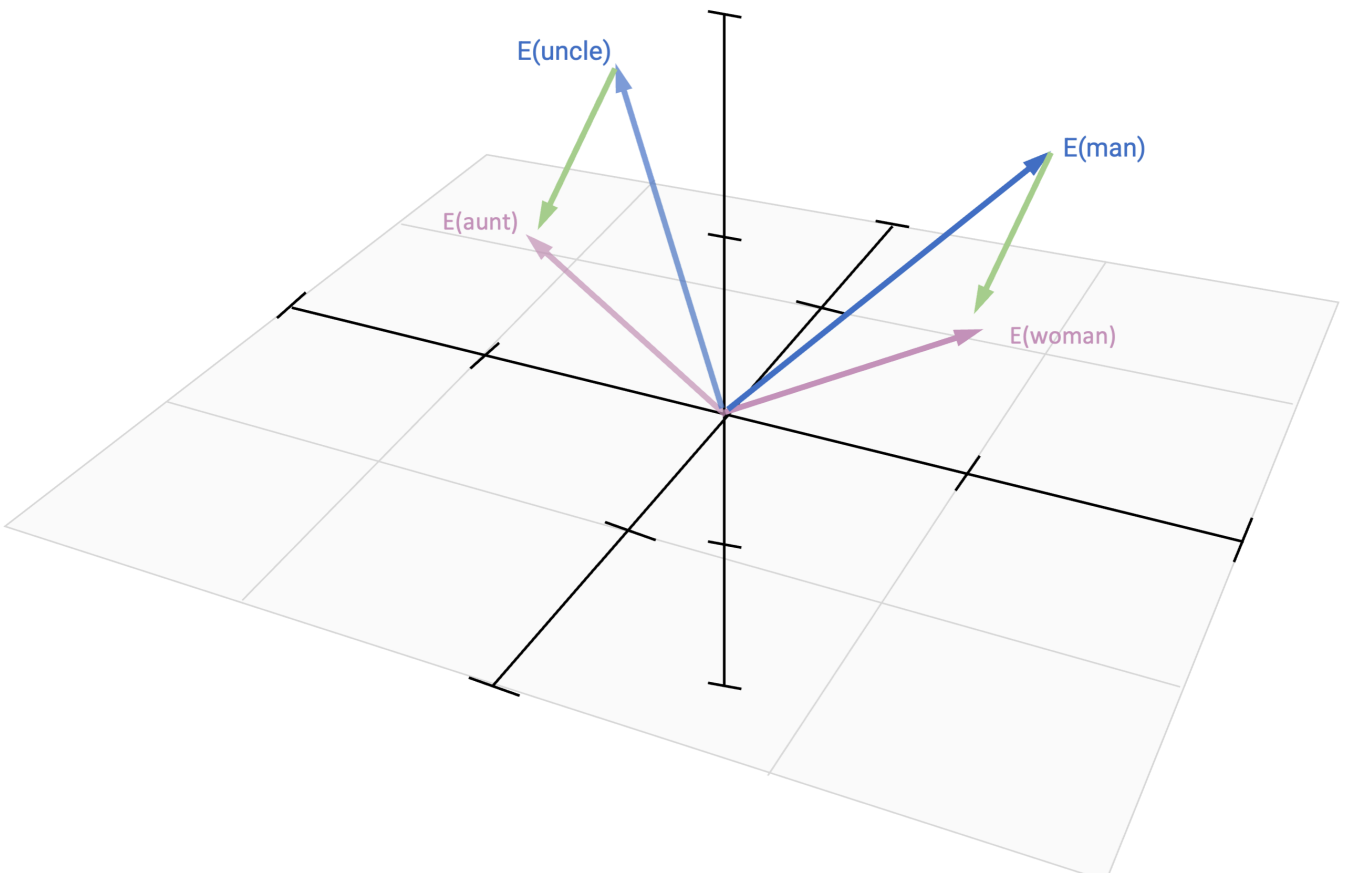
```r
glove_fn = "glove.6B.50d.10k.w2v.txt"
url = glue::glue("https://cssbook.net/d/{glove_fn}")
if (!file.exists(glove_fn))
    download.file(url, glove_fn)

# Data wrangling
wv_tibble <- read_delim(glove_fn, skip=1, delim=" ", quote="",
    col_names = c("word", paste0("d", 1:50)))

# 10 highest scoring words on dimension 1
wv_tibble |>
  arrange(-d1) |> head()
```

```
# A tibble: 6 × 51
  word      d1     d2     d3      d4      d5     d6      d7     d8     d9    d10
  <chr>  <dbl>  <dbl>  <dbl>   <dbl>   <dbl>  <dbl>   <dbl>  <dbl>  <dbl>  <dbl>
1 airbus  2.60 -0.536  0.414  0.339  -0.0510  0.848 -0.722  -0.361  0.869 -0.731
2 space…  2.52  0.744  1.66   0.0591 -0.252  -0.243 -0.594  -0.417  0.460 -0.124
3 fiat    2.29 -1.15   0.488  0.518   0.312  -0.132  0.0520 -0.661 -0.859  0.263
4 naples  2.27 -0.106 -1.27  -0.0932 -0.437  -1.18  -0.0858  0.469 -1.08  -0.549
5 di      2.24 -0.603 -1.47   0.354   0.244  -1.09   0.357  -0.331 -0.564  0.428
6 planes  2.20 -0.831  1.34  -0.348  -0.209  -0.282 -0.824  -0.481  0.211 -0.748
# ℹ 40 more variables: d11 <dbl>, d12 <dbl>, d13 <dbl>, d14 <dbl>, d15 <dbl>,
#   d16 <dbl>, d17 <dbl>, d18 <dbl>, d19 <dbl>, d20 <dbl>, d21 <dbl>,
#   d22 <dbl>, d23 <dbl>, d24 <dbl>, d25 <dbl>, d26 <dbl>, d27 <dbl>,
#   d28 <dbl>, d29 <dbl>, d30 <dbl>, d31 <dbl>, d32 <dbl>, d33 <dbl>,
#   d34 <dbl>, d35 <dbl>, d36 <dbl>, d37 <dbl>, d38 <dbl>, d39 <dbl>,
#   d40 <dbl>, d41 <dbl>, d42 <dbl>, d43 <dbl>, d44 <dbl>, d45 <dbl>,
#   d46 <dbl>, d47 <dbl>, d48 <dbl>, d49 <dbl>, d50 <dbl>
```

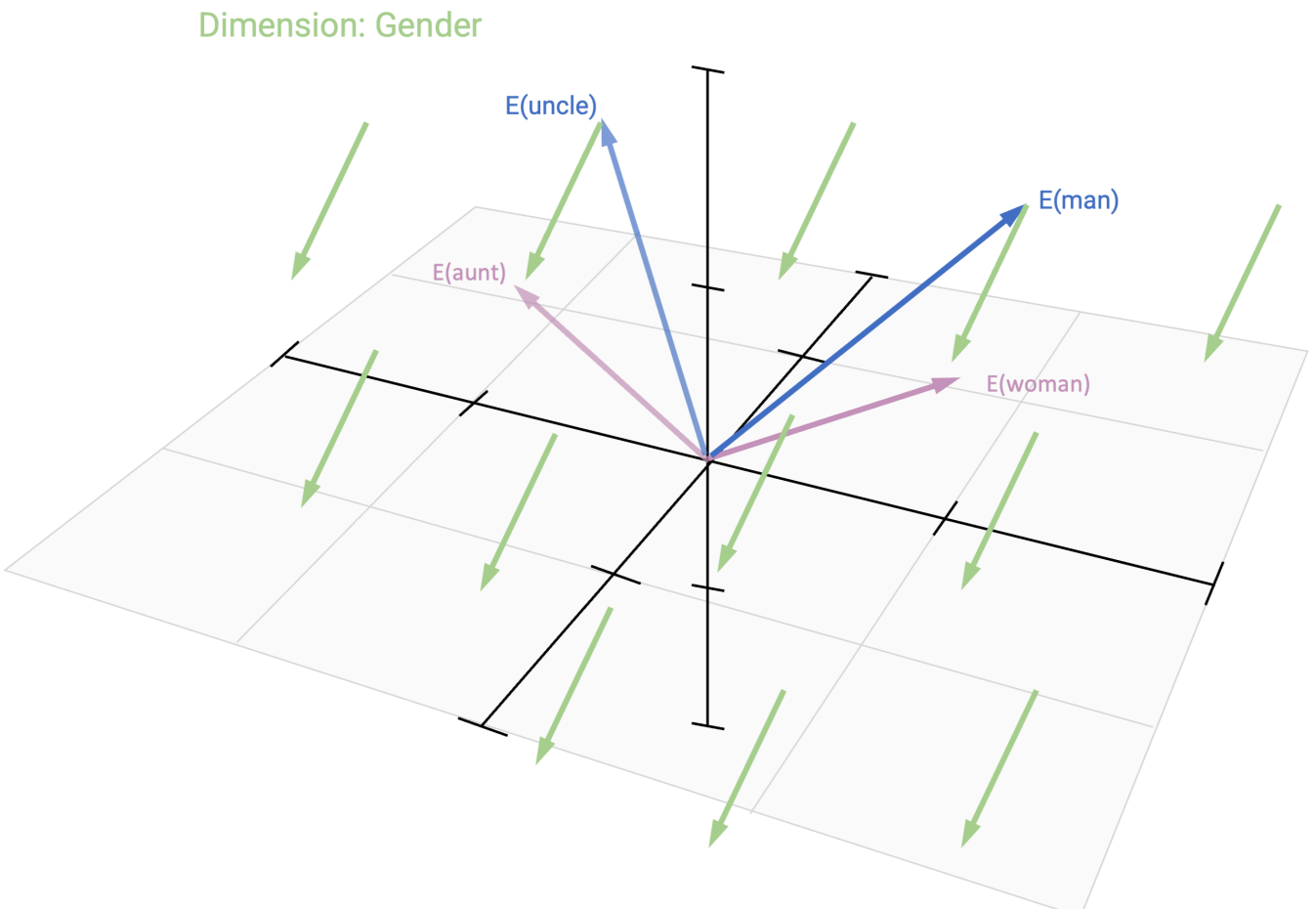
WORDS IN A MULTIDIMENSIONAL VECTOR SPACE



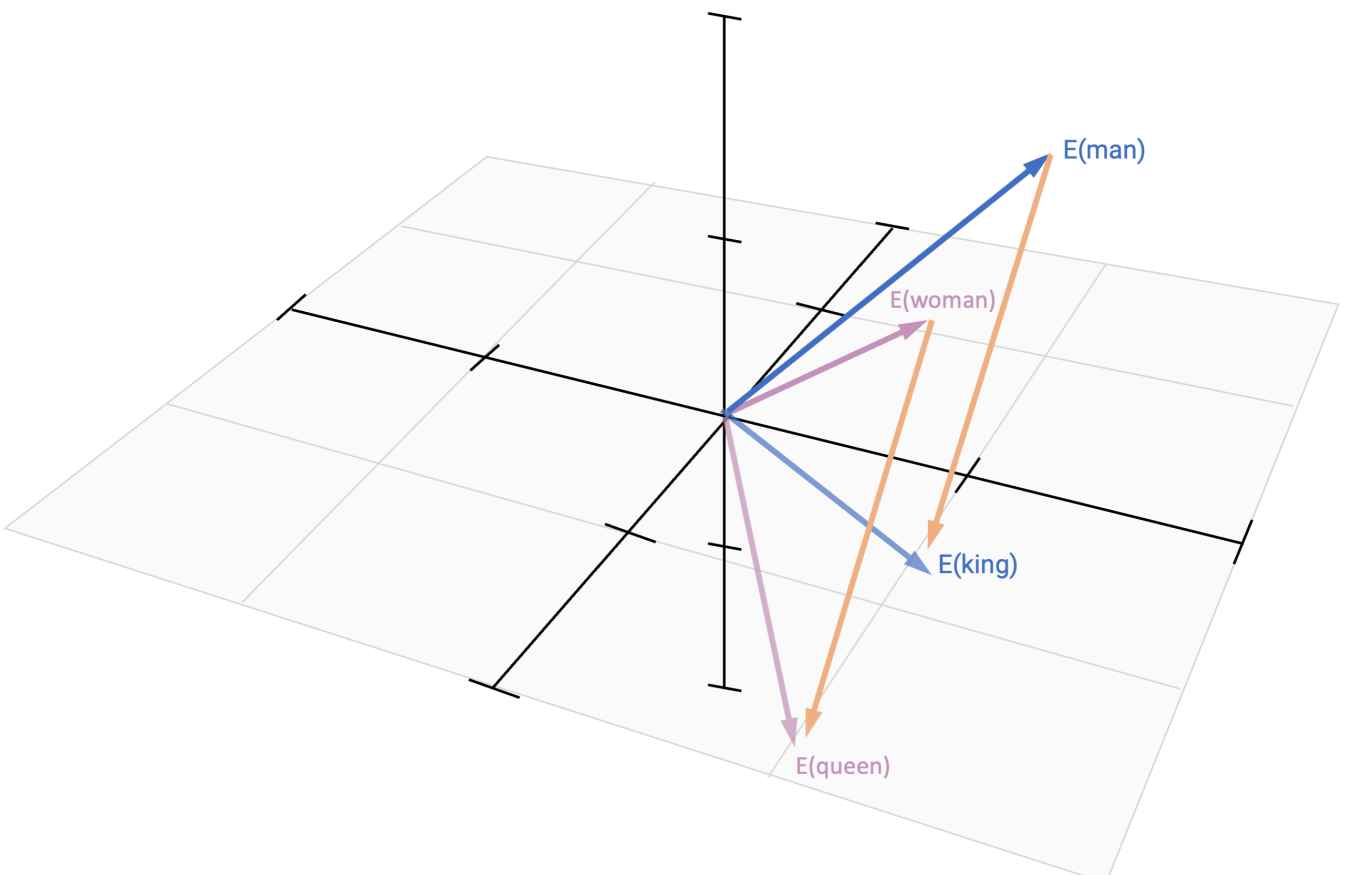
SIMILAR WORDS HAVE SIMILAR CHARACTERISTICS



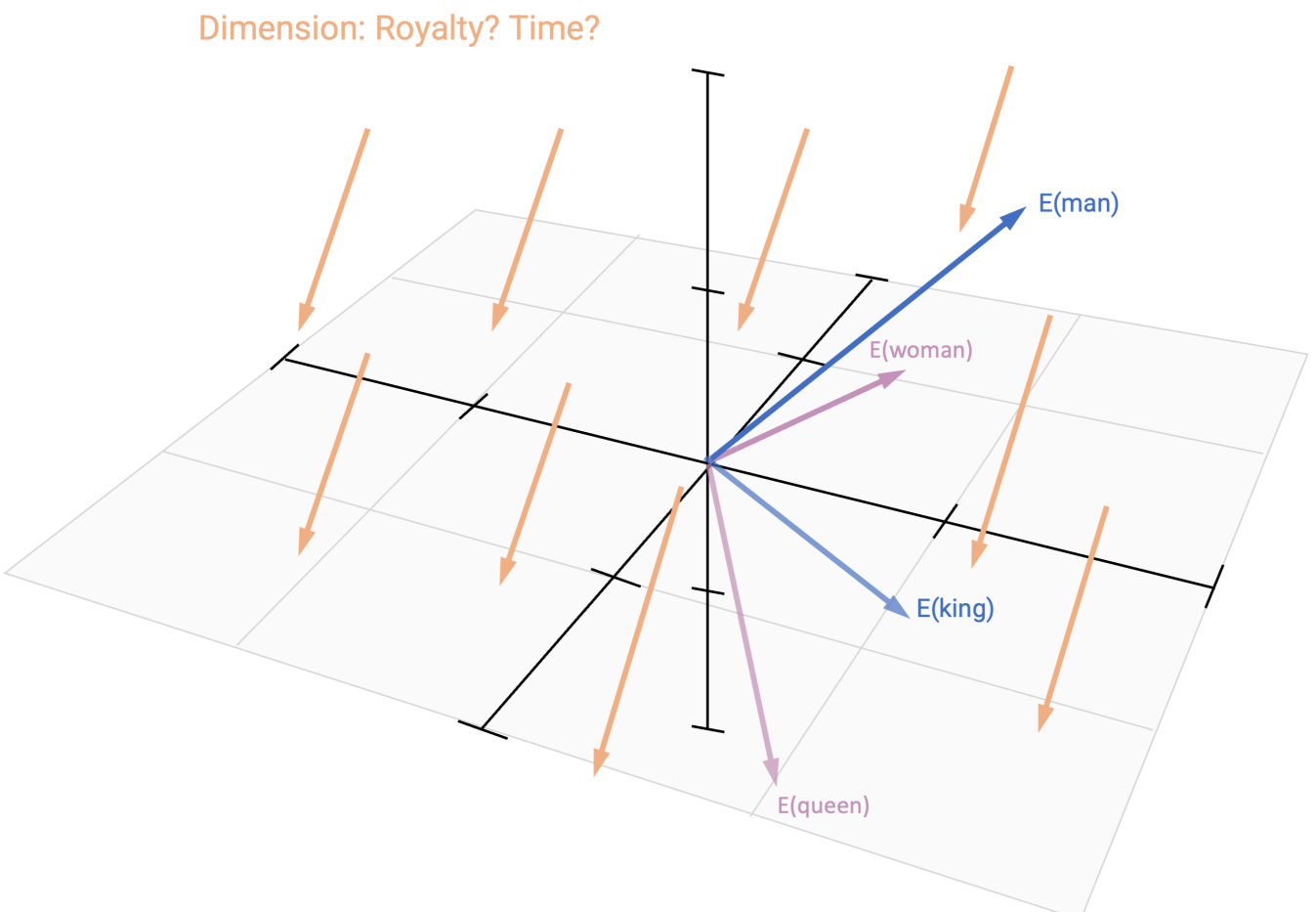
MULTIDIMENSIONAL VECTOR SPACE



MULTIDIMENSIONAL VECTOR SPACE



MULTIDIMENSIONAL VECTOR SPACE



SIMILARITIES BETWEEN WORDS

With word-embeddings, we can compute similarity scores for word pairs, which proves the "encoding of meaning" in word-embeddings:

```r
wv <- as.matrix(wv_tibble[-1])
rownames(wv) <- wv_tibble$word
wv <- wv / sqrt(rowSums(wv^2))
wvector <- function(wv, word) wv[word,,drop=F]
wv_similar <- function(wv, target, n=5) {
  similarities = wv %*% t(target)
  similarities |>
    as_tibble(rownames = "word") |>
    rename(similarity=2) |>
    arrange(-similarity) |>
    head(n=n)
}
```

```r
wv_similar(wv, wvector(wv, "basketball"))
```

```
# A tibble: 5 × 2
  word       similarity
  <chr>           <dbl>
1 basketball      1
2 football        0.879
3 hockey          0.862
4 baseball        0.861
5 nba             0.838
```

```r
wv_similar(wv, wvector(wv, "netherlands"))
```

```
# A tibble: 5 × 2
  word        similarity
  <chr>            <dbl>
1 netherlands      1
2 belgium          0.893
3 switzerland      0.821
4 denmark          0.809
5 france           0.789
```

SIMILARITY OF ENTIRE SENTENCES OR TEXTS

But we can also generalize word embeddings to entire sentences (or even texts):

```r
library(ccsamsterdamR)

# Example sentences
movies <- tibble(sentences = c("This movie is great, I loved it.",
                               "The film was fantastic, a real treat!",
                               "I did not like this movie, it was not great.",
                               "Today, I went to the cinema and watched a movie",
                               "I had pizza for lunch.",
                               "Sometimes, when I read a book, I get completely lost."))

# Get embeddings from a sentence transformer
movie_embeddings <- hf_embeddings(txt = movies$sentences)

# Each text has now 384 values
movie_embeddings
```

```
# A tibble: 6 × 384
       V1       V2      V3       V4      V5       V6       V7      V8      V9      V10     V11      V12      V13
    <dbl>    <dbl>   <dbl>    <dbl>   <dbl>    <dbl>    <dbl>   <dbl>   <dbl>    <dbl>   <dbl>    <dbl>    <dbl>
1 -0.0875 -0.0156  -0.0380 -0.0586  -0.0842  0.0164  -0.0222   0.0451  0.0449 -0.00546 -0.0115 -0.00166  0.00575
2 -0.0544  0.0381  -0.0443 -0.0111  -0.0464 -0.00760 -0.0523   0.0173 -0.0725 -0.0432   0.0206  0.00903  0.0223
3 -0.0838  0.0135  -0.0938 -0.0351  -0.0848 -0.0424  -0.00107  0.0537  0.0559 -0.0729   0.0153  0.0359   0.0396
4 -0.0442  0.00655  0.0754 -0.0341   0.0637  0.00674  0.0993  -0.0369  0.0752 -0.0405   0.0222  0.0284  -0.0243
5 -0.0257  0.0440   0.0407  0.00391 -0.0818 -0.0621   0.0836  -0.0138 -0.101  -0.0757   0.0882 -0.0530   0.0351
6  0.0207  0.00907 -0.0388  0.0717   0.0419  0.0419   0.0267   0.0685  0.0879 -0.0125   0.0281  0.0503  -0.0437
# ℹ 371 more variables: V14 <dbl>, V15 <dbl>, V16 <dbl>, V17 <dbl>, V18 <dbl>, V19 <dbl>, V20 <dbl>, V21 <dbl>,
#   V22 <dbl>, V23 <dbl>, V24 <dbl>, V25 <dbl>, V26 <dbl>, V27 <dbl>, V28 <dbl>, V29 <dbl>, V30 <dbl>, V31 <dbl>,
#   V32 <dbl>, V33 <dbl>, V34 <dbl>, V35 <dbl>, V36 <dbl>, V37 <dbl>, V38 <dbl>, V39 <dbl>, V40 <dbl>, V41 <dbl>,
#   V42 <dbl>, V43 <dbl>, V44 <dbl>, V45 <dbl>, V46 <dbl>, V47 <dbl>, V48 <dbl>, V49 <dbl>, V50 <dbl>, V51 <dbl>,
#   V52 <dbl>, V53 <dbl>, V54 <dbl>, V55 <dbl>, V56 <dbl>, V57 <dbl>, V58 <dbl>, V59 <dbl>, V60 <dbl>, V61 <dbl>,
#   V62 <dbl>, V63 <dbl>, V64 <dbl>, V65 <dbl>, V66 <dbl>, V67 <dbl>, V68 <dbl>, V69 <dbl>, V70 <dbl>, V71 <dbl>,
#   V72 <dbl>, V73 <dbl>, V74 <dbl>, V75 <dbl>, V76 <dbl>, V77 <dbl>, V78 <dbl>, V79 <dbl>, V80 <dbl>, V81 <dbl>, …
```

THE SUBTLE SIMILARITY OF SOME TEXTS IN THE EXAMPLE

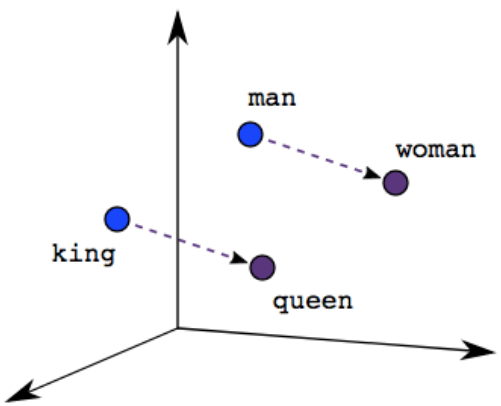
- We can see that text 2 is most similar to text 1: Both express a very similar sentiment, just with different words (“great” ≈ “fantastic”; “I loved it” ≈ “A real treat”)
- Text 2 is still similar to text 3 (after all it is about movies), but less so compared to text 1 (“fantastic” is the opposite of “not great”)
- Text 4 still shares similarities (the context is the cinema/watching movies), but text 5 is very different as it doesn’t contain similar words and is not about similar things (except “I”).
- Text 5 is very dissimilar to the others.

```
# Similarity between 2nd and the other sentences
movies |>
  mutate(similarity = as.matrix(movie_embeddings) %*% t(as.matrix(movie_embeddings)[2,, drop = F])) |>
  arrange(-similarity)
```

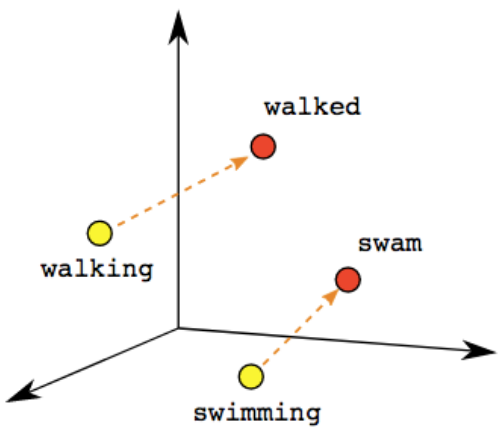
```
# A tibble: 6 × 2
  sentences                                              similarity[,1]
  <chr>                                                           <dbl>
1 The film was fantastic, a real treat!                          1.00
2 This movie is great, I loved it.                               0.646
3 I did not like this movie, it was not great.                   0.513
4 Today, I went to the cinema and watched a movie                0.372
5 I had pizza for lunch.                                         0.132
6 Sometimes, when I read a book, I get completely lost.          0.0939
```

DOING ANALYSIS WITH WORD-EMBEDDING THEMSELVES

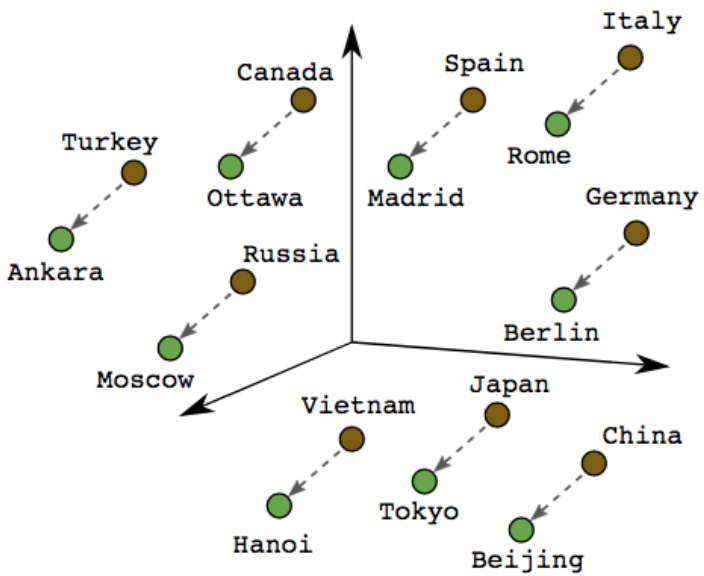
- Based on vector-based computations, we can analyse semantic relationships
- This is a quite common approach by now in research on gender and other types of stereotypes



Male-Female



Verb Tense

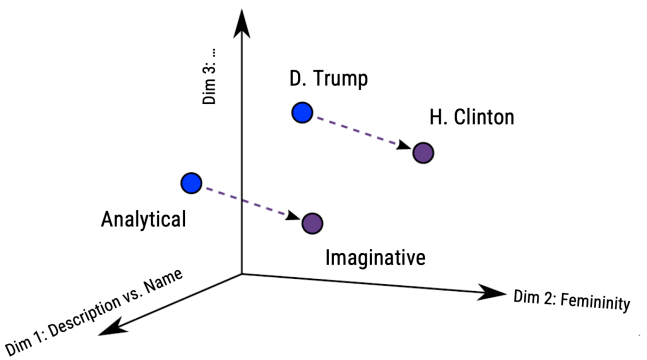


Country-Capital

Source: https://developers.google.com

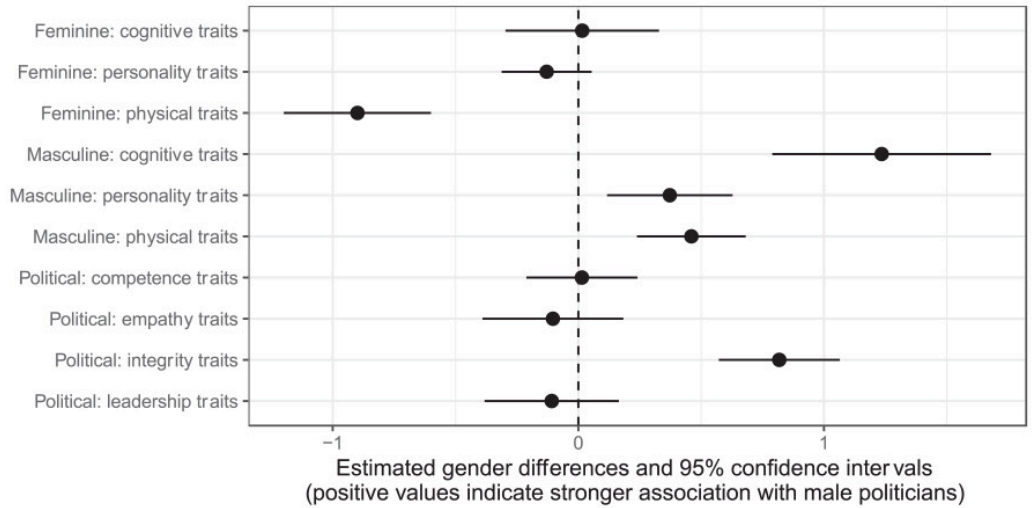
EXAMPLE FROM THE LITERATURE: GENDER-STEREOTYPES

- Andrich et al. (2023) examine stereotypical traits in portrayals of 1,095 U.S. politicians.
- Analyzed 5 million U.S. news stories published from 2010 to 2020 to study gender-linked (feminine, masculine) and political (leadership, competence, integrity, empathy) traits



- Methodologically, they estimated word embeddings using the Continuous Bag of Words (CBOW) model, meaning that a target word (e.g., honest) is predicted from its context (e.g., Who thinks President Trump is [target word]?)
- Bias can thus be identified if e.g., gender-neutral words (e.g., competent) are closer to words that represent one gender (e.g., donald_trump) than to words that represent the opposite gender (e.g., hillary_clinton).

RESULTS



- All three masculine traits were more strongly associated with male politicians.
- In contrast, only the feminine physical traits were more strongly associated with female politicians.
- Differences remained stable across time.

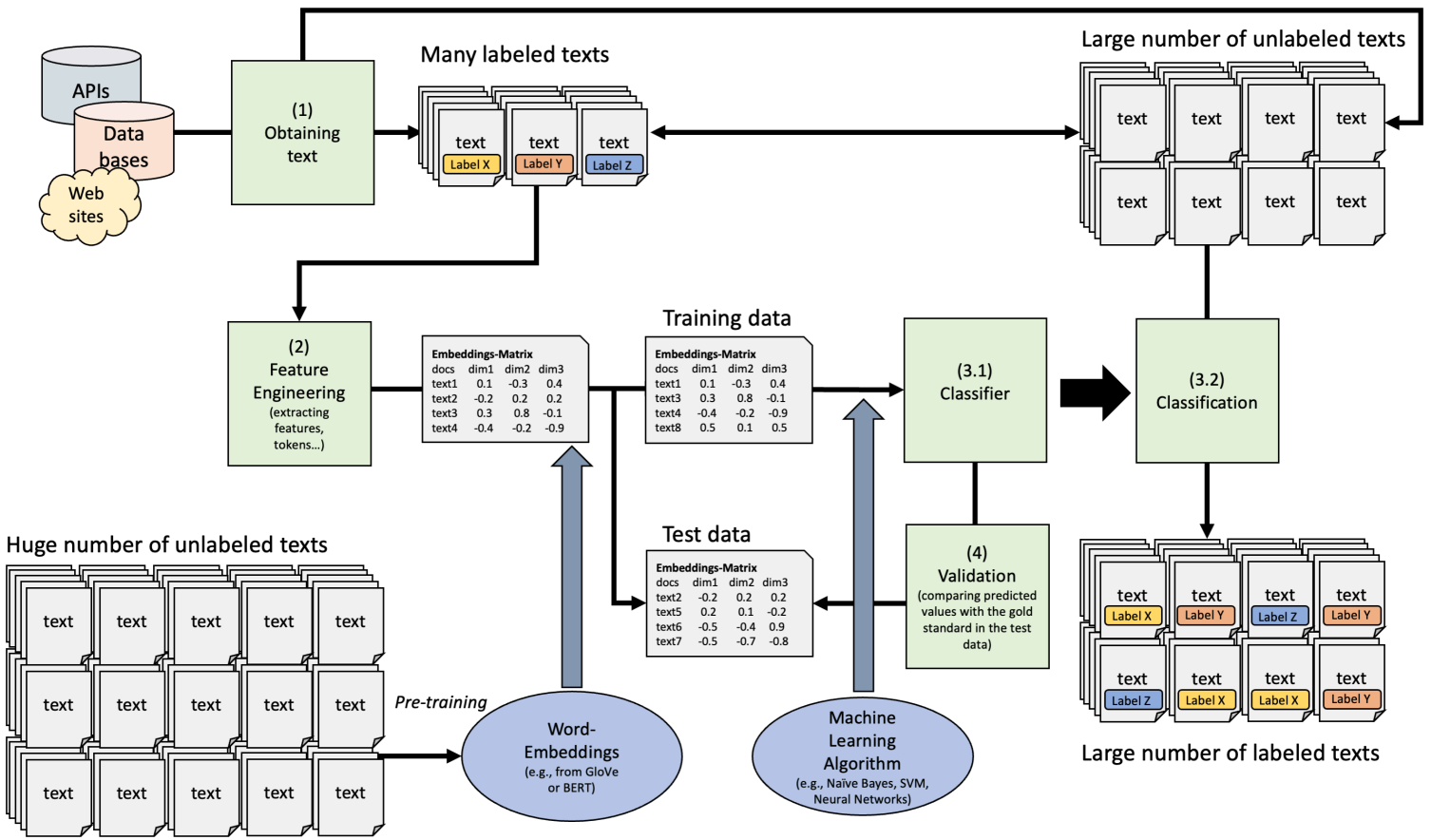
Text Classification with Word-Embeddings

Improving Prediction by Using Word-Embeddings as Input Features

WORD EMBEDDINGS AS INPUT TO CLASSIC ML MODELS

- Word, sentence, or text embedding vectors can then be used as features in further text analysis tasks
- Think about the example we just investigated: The sentence embeddings did capture some difference between:
  - “The film was fantastic, a real treat!” (*positive*)
  - “I did not like this moive, it was not great.” (*negative*)
- Approaches from the last lecture (classic machine learning) would have a hard time to detect the negation “not great”.
- Yet, bear in mind: We do not actually know what the 100+ (often >300) dimensions actually mean (→ we cannot look under the hood later!)

TEXT CLASSIFICATION WITH WORD-EMBEDDINGS

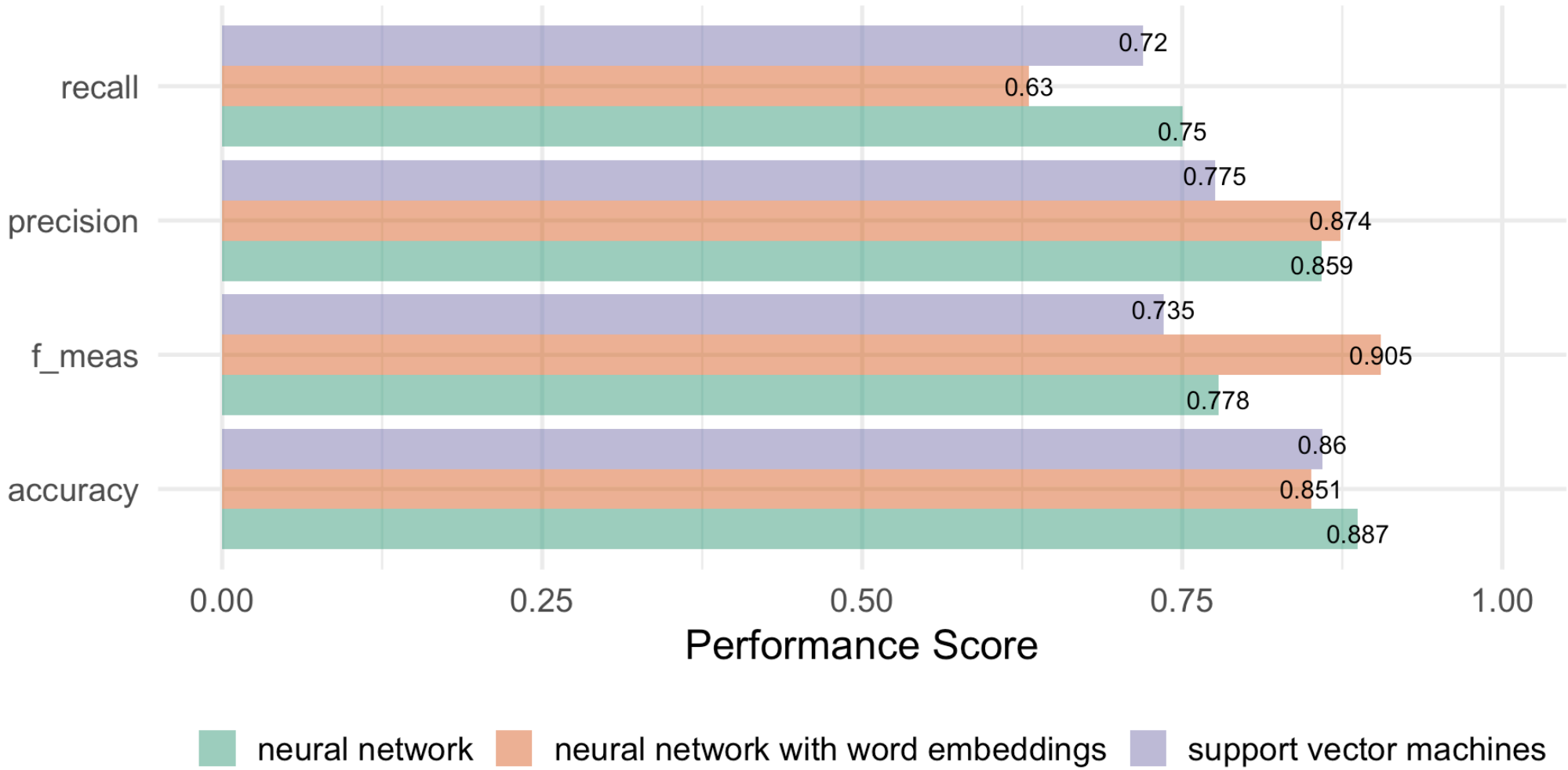


FITTING A NEURAL NETWORK ON WORD-EMBEDDINGS

- To fit a neural network based on static word-embeddings (e.g., GloVe), we only need to adapt the recipe.
- Here, we do not need to engage in much preprocessing at all:

```
# Load GloVe embeddings (50-dimensional)
wv_tibble <- readr::read_delim("slides/GloVe 6B/glove.6B.300d.txt",
                               skip=1, delim=" ", quote="", col_names = c("word", paste0("d", 1:100)))

# Set up the recipe for text preprocessing with GloVe embeddings
text_rec <- recipe(label ~ text, data = science_data) |>
  step_tokenize(text) |>
  step_word_embeddings(text, embeddings = wv_tibble, aggregation = "mean") # <-- Here, I am adding the word-embeddings

# Define the MLP model specification
mlp_spec <-
  mlp(epochs = 400,          # <- times that algorithm will work through train set
      hidden_units = c(6),   # <- nodes in hidden units
      penalty = 0.01,        # <- regularization
      learn_rate = 0.2) |>   # <- shrinkage
  set_engine("brulee") |>    # <-- engine = R package
  set_mode("classification")

# Create workflow
mlp_wflow <- workflow()  |>
  add_recipe(text_rec) |>
  add_model(mlp_spec)

# Fit the workflow on the training data
mlp_fit <- mlp_wflow |>
  fit(data = train_data)
```

COMPARISON WITH THE TWO PREVIOUS APPROACHES



FINE-TUNING PREPROCESSING AND HYPERPARAMETER

- You may have noticed that I always set some **hyperparameter** in all of the models
- There is no clear rule of how to set these parameters and their influence on performance is often unknown
- We have to simply try out whether a neural network needs more than one hidden layer or how many nodes make sense, what learning rate works best, etc.
- Good machine learning practice is to conduct a so-called **grid-search**, i.e. systematically run combinations of different specifications (but computationally expensive!!!)

Hvitfeld & Silge (2021)

GRID SEARCH FOR BEST NEURAL NETWORK ARCHITECTURE

```
# First, we update our model specification
mlp_spec <- mlp(hidden_units = tune(),   # <-- instead of fixed numbers, we set it to "tune"
                penalty = tune(),
                epochs = tune(),
                learn_rate = tune()) |>
  set_engine("brulee", trace = 0) |>
  set_mode("classification")
```

GRID SEARCH: SETTING SPECIFIC PARAMETERS

```r
# First, we update our model specification
mlp_spec <- mlp(hidden_units = tune(),   # <-- instead of fixed numbers, we set it to "tune"
                penalty = tune(),
                epochs = tune(),
                learn_rate = tune()) |>
  set_engine("brulee", trace = 0) |>
  set_mode("classification")

# Estract "dials" for parameter tuning
mlp_param <- extract_parameter_set_dials(mlp_spec)

# Simple combinatorial design
mlp_param |> grid_regular(levels = c(hidden_units = 2, penalty = 2, epochs = 2, learn_rate = 2))
```

```
# A tibble: 16 × 4
   hidden_units      penalty epochs learn_rate
          <int>        <dbl>  <int>      <dbl>
 1            1 0.0000000001      5      0.001
 2           10 0.0000000001      5      0.001
 3            1 1                 5      0.001
 4           10 1                 5      0.001
 5            1 0.0000000001    500      0.001
 6           10 0.0000000001    500      0.001
 7            1 1               500      0.001
 8           10 1               500      0.001
 9            1 0.0000000001      5      0.316
10           10 0.0000000001      5      0.316
11            1 1                 5      0.316
12           10 1                 5      0.316
13            1 0.0000000001    500      0.316
14           10 0.0000000001    500      0.316
15            1 1               500      0.316
16           10 1               500      0.316
```

RUNNING THE GRID SEARCH

```
# Combine the recipe and model into a workflow
mlp_wflow <- workflow() %>%
  add_recipe(text_rec) %>%
  add_model(mlp_spec)

# Set workflow with "dials"
mlp_param <- mlp_wflow  |>
  extract_parameter_set_dials() |>
  update(epochs = epochs(c(100, 400)),
         hidden_units = hidden_units(c(12, 64)),
         penalty = penalty(c(-10, -1)),
         learn_rate = learn_rate(range = c(-10, -1), trans = transform_log10()))

# Set metric of interest
acc <- metric_set(accuracy)

# Define resampling strategy
twofold <- vfold_cv(train_data, v = 2)

# Run the tuning process
mlp_reg_tune <- mlp_wflow  |>
  tune_grid(
    resamples = twofold,
    grid = mlp_param  |>
      grid_regular(levels = c(hidden_units = 2, penalty = 2,    # <-- here, we set specific combination of parameters
                              epochs = 2, learn_rate = 2)),     #     instead, we could also use the `grid_random()`functi
    metrics = acc
  )
```

EVALUATION

- The result of this tuning grid search is a table that shows the best combinations of parameters in descending order
- We can see here that 64 nodes, a very low penalty, a learning rate of 0.1 provides the best performance.

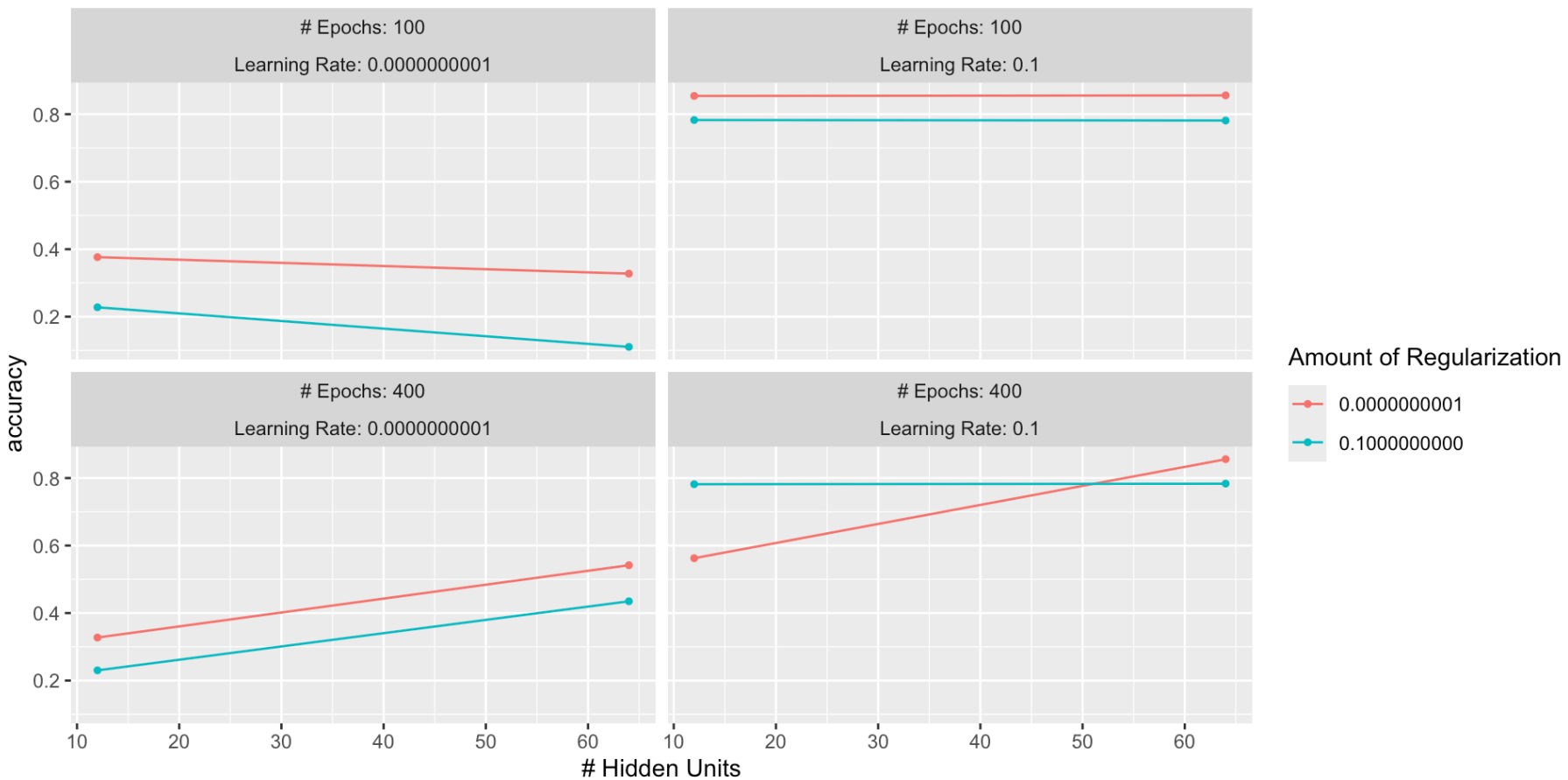
```
best_fit <- show_best(mlp_reg_tune, n = 48) |>
  select(-.estimator, -.config, -.metric) |>
  rename(accuracy = mean)
best_fit
```

```
# A tibble: 16 × 7
   hidden_units      penalty epochs   learn_rate accuracy     n  std_err
          <int>        <dbl>  <int>        <dbl>    <dbl> <int>    <dbl>
 1           64 0.0000000001    400 0.1              0.856     2 0.00406
 2           64 0.0000000001    100 0.1              0.856     2 0.000980
 3           12 0.0000000001    100 0.1              0.854     2 0.00406
 4           64 0.1             400 0.1              0.784     2 0.00245
 5           12 0.1             100 0.1              0.783     2 0.00287
 6           12 0.1             400 0.1              0.782     2 0.00357
 7           64 0.1             100 0.1              0.781     2 0.00371
 8           12 0.0000000001    400 0.1              0.563     2 0.295
 9           64 0.0000000001    400 0.0000000001     0.542     2 0.00154
10           64 0.1             400 0.0000000001     0.435     2 0.106
11           12 0.0000000001    100 0.0000000001     0.376     2 0.0277
12           64 0.0000000001    100 0.0000000001     0.328     2 0.216
13           12 0.0000000001    400 0.0000000001     0.327     2 0.216
14           12 0.1             400 0.0000000001     0.230     2 0.119
15           12 0.1             100 0.0000000001     0.228     2 0.120
16           64 0.1             100 0.0000000001     0.110     2 0.00126
```

EVALUATION

- The effect of parameters becomes even more clear, when we visualize the grid search:

```
1 options(scipen = 999)
2 autoplot(mlp_reg_tune)
```



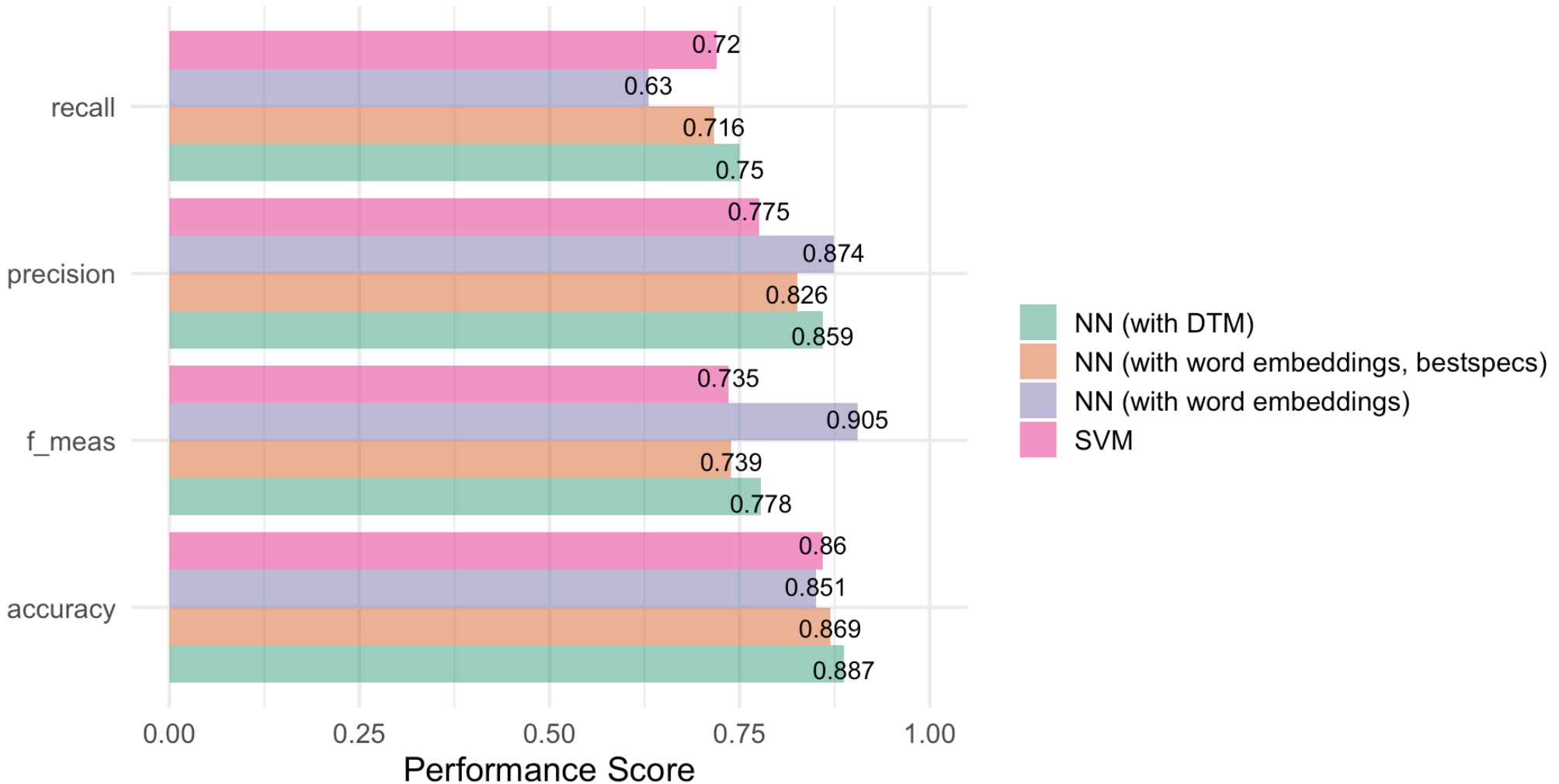
FITTING THE BEST MODEL

```r
mlp_best <-
  mlp(epochs = 400,           # <- times that algorithm will work through train set
      hidden_units = c(64),   # <- nodes in hidden units
      penalty = 0.001,        # <- regularization
      learn_rate = 0.1) |>    # <- shrinkage
  set_engine("brulee") |>     # <-- engine = R package
  set_mode("classification")

# Create workflow
mlp_wflow_best <- workflow()  |>
  add_recipe(text_rec) |>
  add_model(mlp_best)

# Fit the workflow on the training data
mlp_fit_best <- mlp_wflow_best |>
  fit(data = train_data)
```

```r
# Make predictions and evaluate on the test set
predictions_best <- predict(mlp_fit_best, new_data = test_data) %>%
  bind_cols(test_data) |>
  mutate(label = factor(label))

predictions_best |>
 class_metrics(truth = label, estimate = .pred_class)
```

```
# A tibble: 4 × 3
  .metric   .estimator .estimate
  <chr>     <chr>          <dbl>
1 accuracy  multiclass     0.869
2 precision macro          0.826
3 recall    macro          0.716
4 f_meas    macro          0.739
```

COMPARISON WITH OTHER APPROACHES



GENERAL DRIVERS OF MODEL PERFORMANCE

1. Task difficulty
2. Amount of training data
3. Choice of features (n-grams, lemmata, etc)
4. Text preprocessing (e.g., exclude or include stopwords?)
5. Representation of text (tf, tf-idf, word-embedding)
6. Tuning of algorithm (what we just did in the grid search)

IMPACT OF TEXT PREPROCESSING ON PERFORMANCE?

- Scharkow ran a simple simulation study in which he systematically varied text preprocessing
- The classifier was always Naive Bayes, below we see the average difference in performance

Table 3 Effects of preprocessing on classification quality for different categories, unstandardized regression coefficients and standard errors

	Kripp. α	Accuracy	Precision	Recall
Stemming	−1.5 (0.5)	−0.5 (0.2)	−0.7 (1.6)	−1.2 (0.8)
Stop word removal	−5.2 (0.5)	−2.6 (0.2)	−4.1 (1.6)	1.1 (0.8)
Text extraction	9.8 (0.5)	3.6 (0.2)	15.6 (1.6)	0.7 (0.8)
Stemming × Stop	0.4 (0.6)	−0.2 (0.3)	−2.0 (1.8)	1.5 (0.9)
Stemming × Text Extr.	−0.4 (0.6)	0.3 (0.3)	−2.3 (1.8)	−0.2 (0.9)
Stop × Text Extr.	−0.2 (0.6)	1.2 (0.3)	0.7 (1.8)	−4.5 (0.9)

Full factorial design with replications, $n = 512$

VALIDITY OF DIFFERENT APPROACHES

- Van Atteveldt et al. (2021) re-analysised data reported in Boukes et al. (2020) to understand the validity of different text classification approaches for sentiment analysis
- The data included news from a total of ten newspapers and five websites published between February 1 and July 7, 2015:
  - three quality newspapers (NRC Handelsblad, Trouw, de Volkskrant)
  - a financial newspaper (Financieel Dagblad)
  - three popular newspapers (Algemeen Dagblad, Metro, De Telegraaf)
  - three regional outlets (Dagblad van het Noorden, de Gelderlander, Noordhollands Dagblad)

MAIN RESULTS

Table 2. Overall performance of the tested sentiment analysis approaches.

				Positive			Neutral			Negative		
section	name	Acc.	alpha	Pr.	Re.	F1	Pr.	Re.	F1	Pr.	Re.	F1
Manual Coding	Single Coder	0.82	0.82	0.88	0.86	0.87	0.76	0.81	0.78	0.84	0.80	0.82
Manual Coding	Vote (3 Coders)	0.88	0.90	0.97	0.91	0.94	0.82	0.88	0.85	0.87	0.84	0.86
Crowd-Coding	Single Coder	0.72	0.75	0.69	0.84	0.76	0.69	0.58	0.63	0.78	0.78	0.78
Crowd-Coding	Vote (3 Coders)	0.77	0.81	0.73	0.89	0.80	0.74	0.65	0.69	0.83	0.81	0.82
Crowd-Coding	Vote (5 Coders)	0.77	0.81	0.73	0.90	0.81	0.73	0.65	0.69	0.84	0.80	0.82
Machine Learning	CNN	0.63	0.50	0.68	0.49	0.56	0.58	0.78	0.66	0.72	0.57	0.63
Machine Learning	NB	0.58	0.39	0.74	0.34	0.47	0.52	0.83	0.64	0.65	0.47	0.55
Machine Learning	SVM	0.57	0.41	0.69	0.37	0.48	0.52	0.79	0.62	0.64	0.48	0.55
Dictionaries	DANEW	0.42	0.10	0.75	0.08	0.15	0.40	0.97	0.57	0.80	0.04	0.08
Dictionaries	DamstraBoukes	0.41	0.05	0.83	0.07	0.13	0.40	0.99	0.57	0.00	0.00	0.00
Dictionaries	Muddiman	0.49	0.31	0.53	0.38	0.44	0.46	0.64	0.53	0.53	0.39	0.45
Dictionaries	NRC	0.47	0.32	0.39	0.53	0.45	0.46	0.44	0.45	0.59	0.46	0.52
Dictionaries	Pattern	0.39	0.07	0.43	0.08	0.14	0.39	0.90	0.54	0.38	0.03	0.06
Dictionaries	Polyglot	0.42	0.26	0.38	0.32	0.34	0.39	0.55	0.45	0.53	0.33	0.41
English Dictionaries	AFINN	0.43	0.27	0.35	0.38	0.37	0.40	0.50	0.45	0.58	0.38	0.46
English Dictionaries	DamstraBoukes	0.42	0.07	0.67	0.08	0.15	0.40	0.98	0.57	1.00	0.02	0.04
English Dictionaries	GenInq	0.41	0.26	0.31	0.37	0.34	0.38	0.38	0.38	0.54	0.47	0.51
English Dictionaries	HuLiu	0.46	0.34	0.40	0.30	0.34	0.42	0.63	0.50	0.65	0.40	0.50
English Dictionaries	LoughranMcDonald	0.50	0.29	0.50	0.14	0.22	0.46	0.79	0.58	0.62	0.43	0.51
English Dictionaries	LSD	0.46	0.33	0.39	0.40	0.39	0.42	0.54	0.48	0.62	0.41	0.50
English Dictionaries	Muddiman	0.48	0.27	0.48	0.38	0.43	0.46	0.71	0.55	0.57	0.30	0.39
English Dictionaries	NRC	0.42	0.23	0.34	0.62	0.44	0.43	0.32	0.37	0.57	0.39	0.46
English Dictionaries	RID	0.42	0.06	0.00	0.00	0.00	0.41	0.97	0.57	0.82	0.09	0.16

Acc.: Accuracy expressed as percentage correct; *α*: Krippendorff's alpha (ordinal), Pr.: Precision for the specified class (Positive/Neutral/Negative); Re.: Recall for that class; F1: F1-Score for that class. When more than one measurement or prediction (respectively for manual/crowd annotation and machine learning) was available, we averaged the score.

Examples from the literature

How Machine Learning is used in Communication Science

EXAMPLE 1: INCIVILITY IN FACEBOOK COMMENTS

- Su et al. (2018) examined the extent and patterns of incivility in the comment sections of 42 US news outlets' Facebook pages in 2015–2016
- News source outlets included
  - National-news outlets (e.g., ABC, CBS, CNN…)
  - Local-new outlets (e.g., The Denver Post, San Francisco Chronicle…)
  - Conservative and liberal partisan news outlets (e.g., Breitbart, The Daily Show…)
- Implemented a combination of manual coding and supervised machine learning to code:
  - Civility
  - Interpersonal rudeness
  - Personal rudeness
  - Impersonal extreme incivility
  - Personal extreme incivility

RESULTS: OVERALL DIFFERENCES

Table 5. Levels and directionality of incivility in comments on the Facebook pages of news outlets.

Pattern	News outlets			
	National	Local	Conservative	Liberal
% Extreme incivility	7	22	19	9
% Personal	4	4	1	<1
% Impersonal	3	18	18	9
% Rudeness	33	19	18	16
% Personal	5	14	7	5
% Impersonal	28	5	11	11
% Civility	60	59	63	75
Total opinions	108,315,349	8,305,639	84,329,761	42,284,889

The analysis period was 1 April 2015 through 30 September 2016.

EXAMPLE 2: ELECTORAL NEWS SHARING IN MEXICO

- de León et al. (2021) explored how elections transform news sharing behaviour on Facebook
- They investigated changes in news coverage and news sharing behaviour on Facebook
  - by comparing election and routine periods, and
  - by addressing the 'news gap' between preferences of journalists and news consumers on social media.
- Employed a novel data set of news articles (N = 83,054) in Mexico
- First coded 2,000 articles manually into topics (Politics, Crime and Disasters, Culture and Entertainment, Economic and Business, Sports, and Other), then used support vector machines to classify the rest

RESULTS

- During periods of heightened political activity, both the publication and dissemination of political news increases
- The gap between the news choices of journalists and consumers narrows, and increased political news sharing leading to a decrease in the sharing of other news.

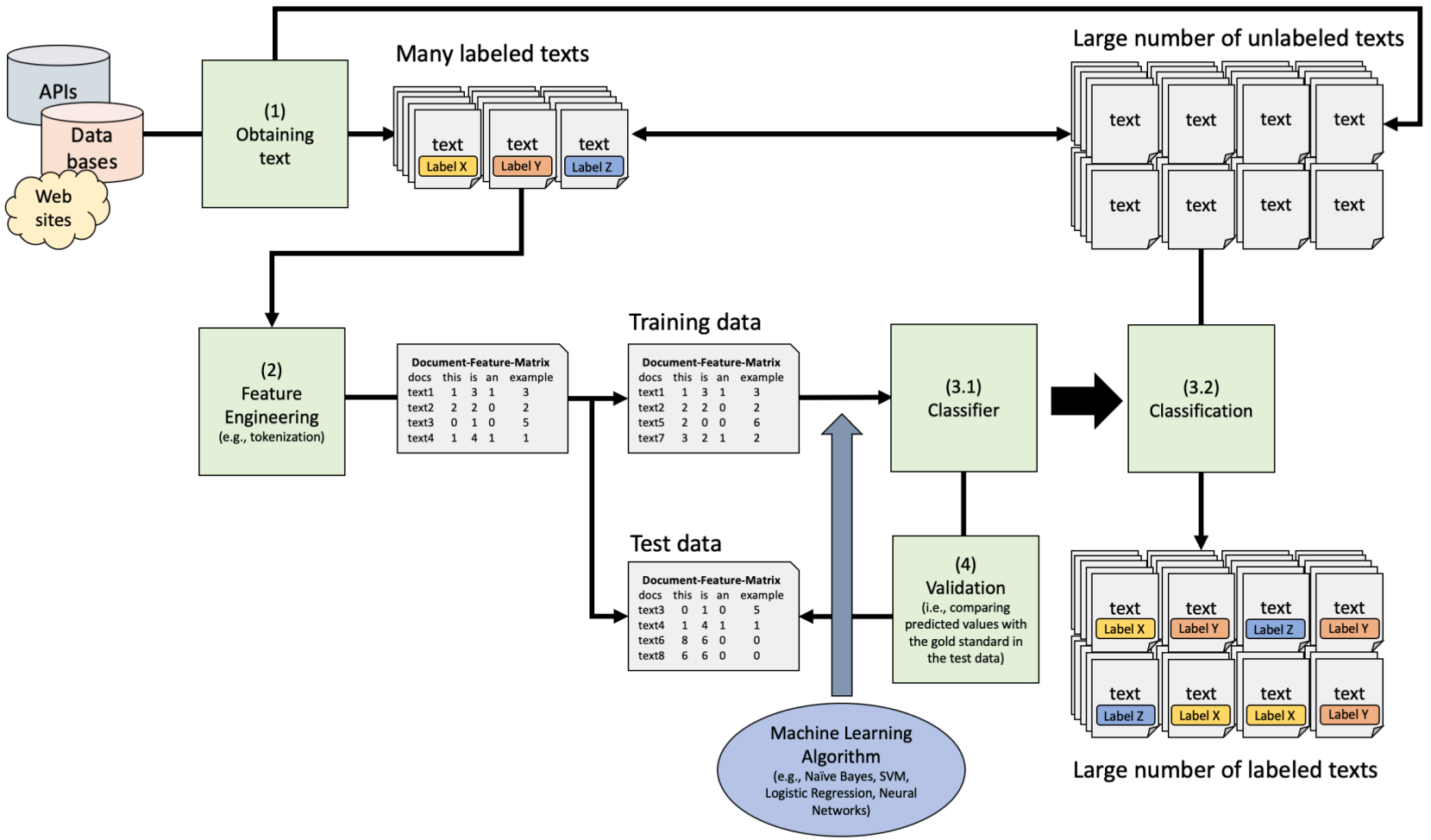
	Topic	Articles		Share				
		Total	Percent	Mean	Median	Max.	Total	Percent
Elections (March–July 2018)	Crimes	7748	17.1% (−2.9)	163.64	1	36,663	1,267,848	14.9% (−10)
	Culture	9841	21.9% (−2.7)	160.80	0	240,395	1,582,357	18.6% (−6.6)
	Economy	3658	8.1% (−1)	116.70	0	30,121	426,887	5% (−1.6)
	Other	1931	4.3% (−0.5)	181.78	1	32,802	351,018	4.1% (−3.7)
	Politics	16,852	37.1% (+5.1)	279.55	0	86,212	4,711,060	55.4% (+21.5)
	Sports	5355	11.8% (+1.9)	31.30	0	29,232	167,602	2% (+0.4)
	Total	45,385	100%	187.44			8,506,772	100%
Routine (March–July 2019)	Crimes	7519	20% (+2.9)	419.36	23	59,077	3,153,181	24.9% (+10)
	Culture	9174	24.5% (+2.7)	346.76	6	107,353	3,181,185	25.2% (+6.6)
	Economy	3414	9.1% (+1)	243.61	0	30,462	831,674	6.6% (+1.6)
	Other	1780	4.7% (+0.5)	555.57	13	117,366	988,909	7.8% (+3.7)
	Politics	12,063	32% (−5.1)	355.74	11	36,221	4,291,265	33.9% (−21.5)
	Sports	3719	9.9% (−1.9)	54.09	1	20,625	201,160	1.6% (−0.4)
	Total	37,669	100%	335.75			12,647,374	100%

Article publication and Facebook sharing by topic, for election and routine periods. Changes between periods indicated in parentheses. Minimum was 0 for all topics in both periods. Note that the Median values may seem remarkably low, but are fully in line with other research on news sharing on Facebook, as especially in non-English and non-international contexts, most news articles do not gain any traction (see Figure 2 in Trilling et al., 2017).

Summary, Conclusion, and Outlook

Next week, we reach the present!

MACHINE LEARNING TEXT CLASSIFICATION PIPELINE



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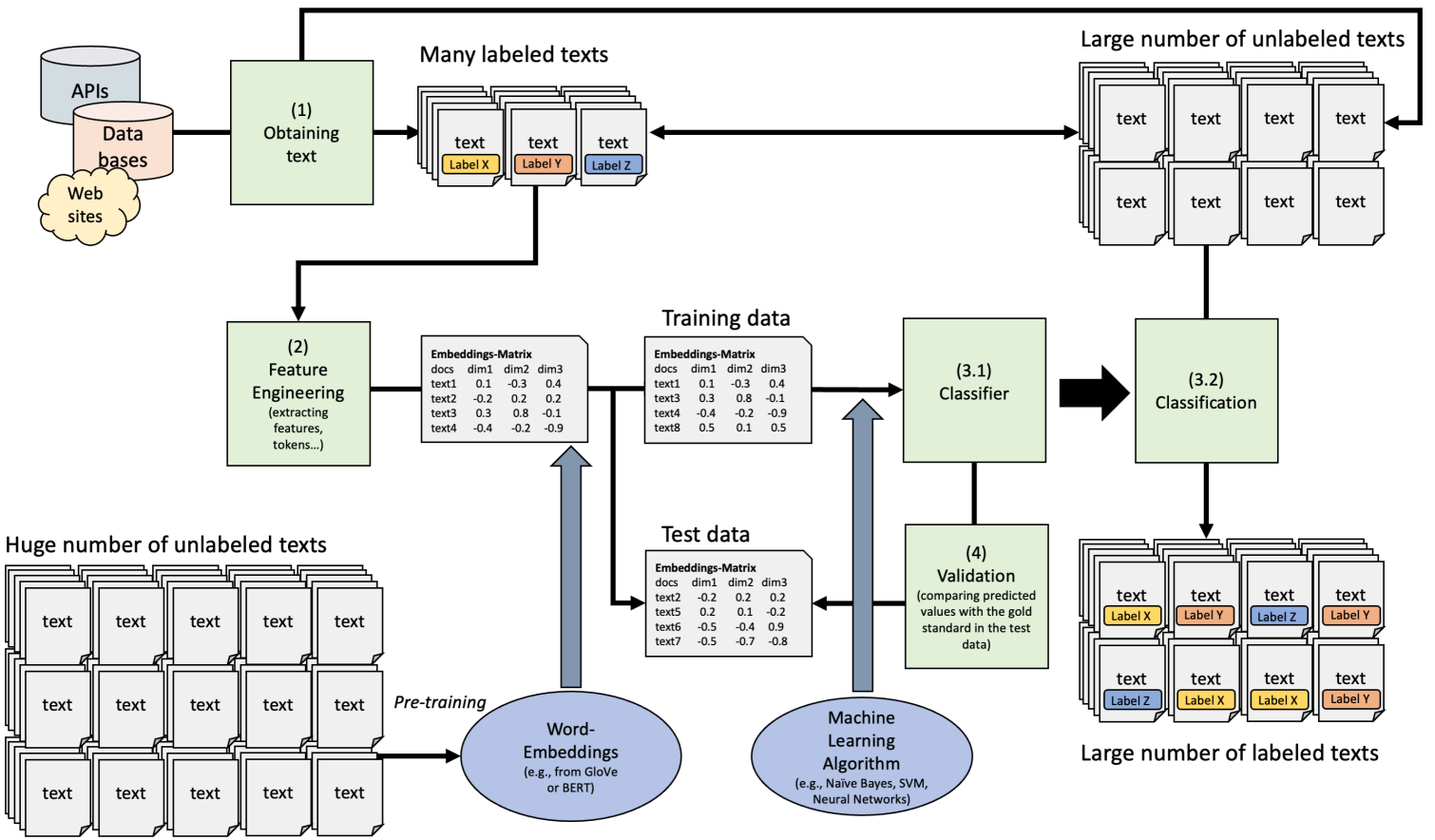

GENERAL CONSIDERATIONS

- Machine learning in the social sciences generally used to solve an engineering problem
- Output of Machine Learning is input for “actual” statistical model (e.g., we classify text, but run an analysis of variance with the output)
- Ethical concerns
  - Is it okay to use a model we can’t possibly understand (e.g., SVM, neural networks)?
  - If they lead to false positives or false negatives, which in turn discriminate someone or lead to bias, it is difficult to find the source and denote responsibility
- We always need to validate model on unseen and representative test data!
- Think before you run models or you will waste a lot of computational resources

CONCLUSION AND OUTLOOK

- Classic machine learning is a useful tool for generalizing from a sample
- It is very useful to reduce the amount of manual coding needed
- Word-Embeddings are a dense representation of text that can improve speed and performance of standard ML approaches
- That said, the field has moved on and innovations are fast-paced these days:
  - Transfer Learning, Attention, Self-Attention…. (Next week!!!)

Thank you for your attention!

REQUIRED READING

van Atteveldt, W., van der Velden, M. A. C. G., & Boukes, M.. (2021). The Validity of Sentiment Analysis: Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms. Communication Methods and Measures, (15)2, 121-140, https://doi.org/10.1080/19312458.2020.1869198

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(available on Canvas)

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EXAMPLE EXAM QUESTION (MULTIPLE CHOICE)

Van Atteveldt and colleagues (2020) tested the validity of various automated text analysis approaches. What was their main result?

A. English dictionaries performed better than Dutch dictionaries in classifying the sentiment of Dutch news paper headlines.

B. Dictionary approaches were as good as machine learning approaches in classifying the sentiment of Dutch news paper headlines.

C. Of all automated approaches, supervised machine learning approaches performed the best in classifying the sentiment of Dutch news paper headlines.

D. Manual coding and supervised machine learning approaches performed similarly well in classifying the sentiment of Dutch news paper headlines.

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EXAMPLE EXAM QUESTION (OPEN FORMAT)

Describe the typical process used in supervised text classification.

Any supervised machine learning procedure to analyze text usually contains at least 4 steps:

1. One has to manually code a small set of documents for whatever variable(s) you care about (e.g., topics, sentiment, source,…).
2. One has to train a machine learning model on the hand-coded /gold-standard data, using the variable as the outcome of interest and the text features of the documents as the predictors.
3. One has to evaluate the effectiveness of the machine learning model via cross-validation. This means one has to test the model test on new (held-out) data.
4. Once one has trained a model with sufficient predictive accuracy, precision and recall, one can apply the model to more documents that have never been hand-coded or use it for the purpose it was designed for (e.g., a spam filter detection software)