AI and Big Data Masterclass for International Management

AOM 2025 PDW 15383

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ECONOMICS
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Introduction to the PDW

Our Panelists

- Jakob Müllner
  - Department of Global Trade, WU Vienna
- Sheen Levine
  - Naveen Jindal School of Management, UT Dallas
  - Management, Technical University of Denmark
- Sima Yue Ling
  - Global Competitiveness Institute, University of Cork
  - Naveen Jindal School of Management, UT Dallas
- Harald Puhr
  - Department of Management and Marketing, University of Innsbruck
  - Department of Global Trade, WU Vienna
- Laurenz Tinhof
  - Department of Global Trade, WU Vienna





Agenda

- Part 1: What do Big Data, Machine Learning, and AI Mean for International Management?
  - 09:30 – 11:10
- Break
  - 11:10 – 11:20
- Part 2: How Can I Use Big Data, Machine Learning, and AI in My Research?
  - 11:20 – 13:30

Agenda – Part 1 (09:30-11:20)

- Big Data and Artificial Intelligence
  - Harald Puhr
- Big Data in Management Research
  - Jakob Müllner
- Strategic Decoupling in International Disputes: Sentiment and Topic Identification with LLMs
  - Sima Yue Ling
- Strategic Decoupling in International Disputes: Text-Embeddings to Discover Cognitive Patterns
  - Sheen Levine
- Valuing Public Goods in a Populist World: Identifying Network Ties
  - Harald Puhr

Agenda – Part 2 (11:30 – 13:30)

- Conceptual Foundations of AI and Machine Learning
  - Harald Puhr
- A Basic Machine Learning Workflow in R
  - Laurenz Tinhof
- Case Study: Predicting Foreign Subsidiary Profits
  - Laurenz Tinhof
- Coffee House Style Discussion

Big Data and Artificial Intelligence

Introduction to Big Data

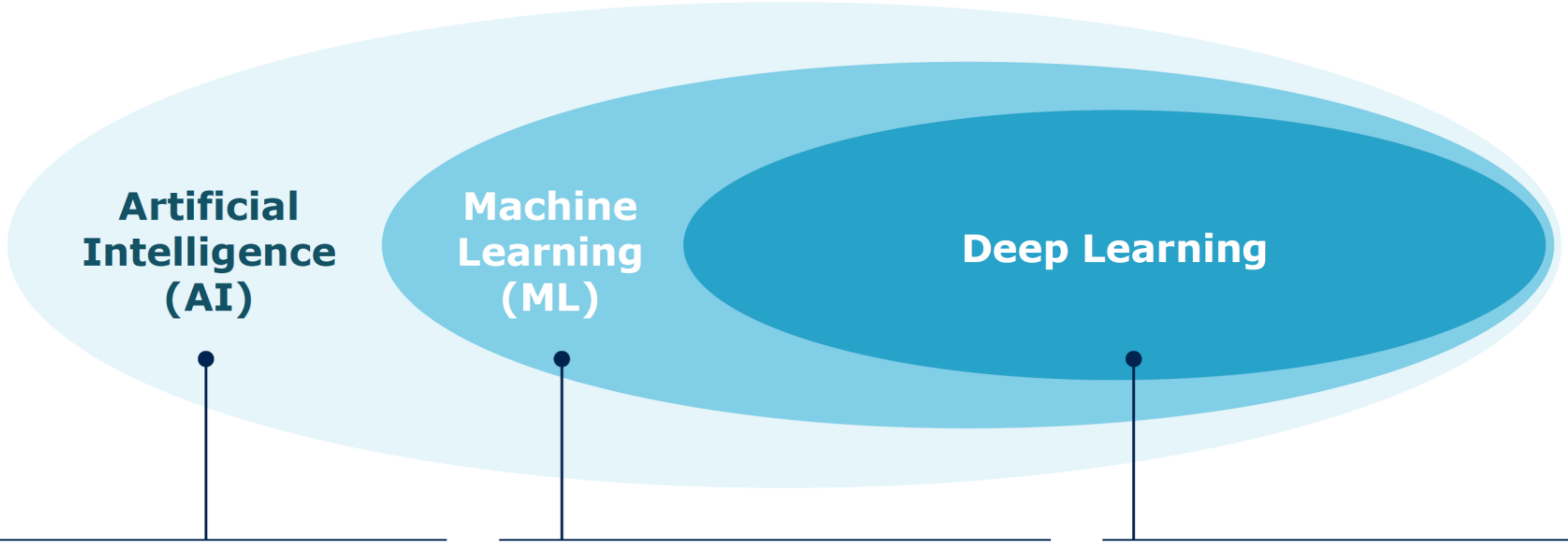
Big Data refers to extremely large, fast-growing, and diverse datasets, structured, semi-structured, and unstructured, that are too complex for traditional data management tools

- This creates challenges for researchers:
  - Data engineering: Big Data requires complex collection and feature engineering
  - Data storage: Data sets with multiple GB of data that slow down processing
  - Data analytics: Too many variables or observations for traditional methods

Examples in social sciences:

- Geo-spatial data
- Network data
- Text mining
- Video and image data
- Game data
- …

Introduction Artificial Intelligence

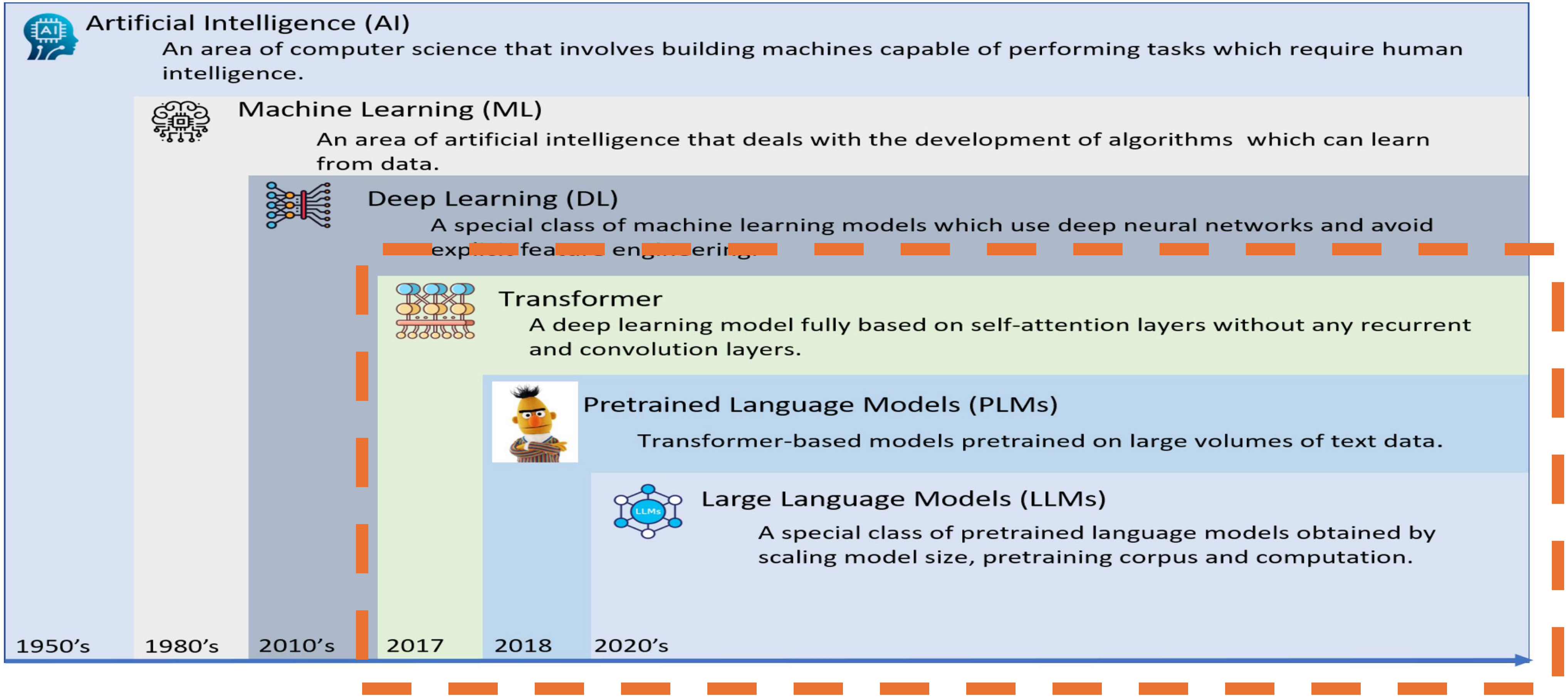


More generally describes **decision-support** that **automates certain thought processes** based on learning and intelligence *(McCarthy, 2007)*

Relates to a **specific set of methods** that **improve automatically through experience** *(Jordan & Mitchell, 2015)*

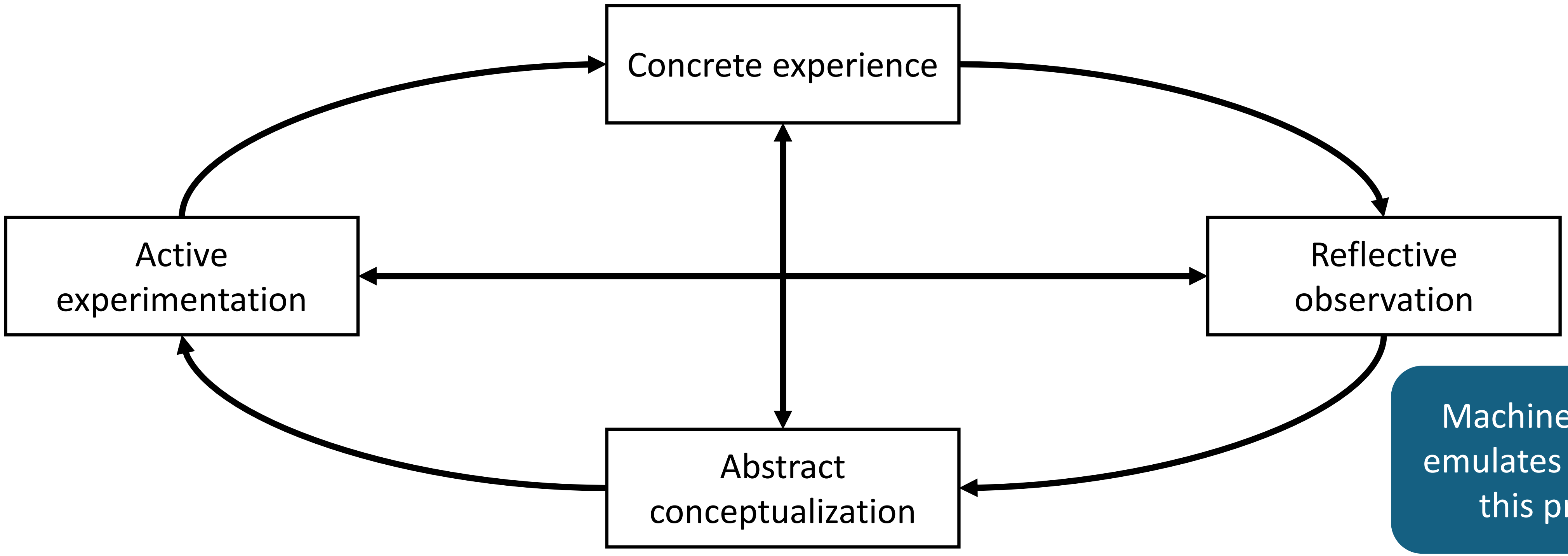
Refers to **specific methods** that compose of **multiple processing layers** to generate levels of abstraction of data *(LeCun, Bengio & Hinton, 2015)*

Introduction Artificial Intelligence



https://doi.org/10.1016/j.nlp.2023.100048

Experiential Learning by Humans



Machine learning emulates aspects of this process.

https://doi.org/10.1177/1350507605058130

Human Learning vs. Machine Learning

- Concrete experience
  - Human: Real-life experiences and encounters made by humans.
  - Machine: Collect the raw material (observations or measurements) from which the model learns.
- Reflective observation
  - Human: Learners reflect on their experience, observing and noting outcomes, patterns, or anomalies.
  - Machine: Analyze the data and understand patterns from the data (model fitting).
- Abstract conceptualization
  - Human: Learners form theories or conceptual frameworks to explain what was observed.
  - Machine: Generalize by defining a functional form that describes the identified relations.
- Active experimentation
  - Human: Learner test their new knowledge by applying it in different situations
  - Machine: Model testing and updating. In machine learning, this is part of the algorithm.

ML as a Method for Quantitative Data Analysis (before)

- **Descriptive statistics**
  - Moments of distributions
  - Correlations
  - Number summaries
  - Other
- **Inferential statistics**
  - Parametric methods (hypothesis testing)
    - Bayesian statistics
    - "Frequentist" statistics
  - Non-parametric methods
    - Many varieties...
- **Machine learning**
  - Explainable ML („parametric")
    - Regressions
    - Support vector machines
    - Random forest models
    - Neural nets
  - ML (focus on prediction)
    - Regressions
    - Support vector machines
    - Random forest models
    - Neural nets

Focus in IB (before)

This Perspective Is Changing Rapidly!

TABLE 1
Machine Learning Strategies for Theoretical Contribution in the Landscape of Management and Organizational Research

	Theoretical fragmentation	Theoretical coherence
Continuous phenomena	*Predictive selection* Finding stable predictors across alternative theories	*Predictive refinement* Refining theory by training and evaluating models on new but similar data
Discontinuous phenomena	*Formative discovery* Patterns in data that give rise to novel (alternative) theory	*Reductive discovery* Patterns in data that show the limit to generalizability of existing theory

Von Krogh, G., Roberson, Q., & Gruber, M. (2023). Recognizing and Utilizing Novel Research Opportunities with Artificial Intelligence. Academy of Management Journal, 66(2), 367-373.

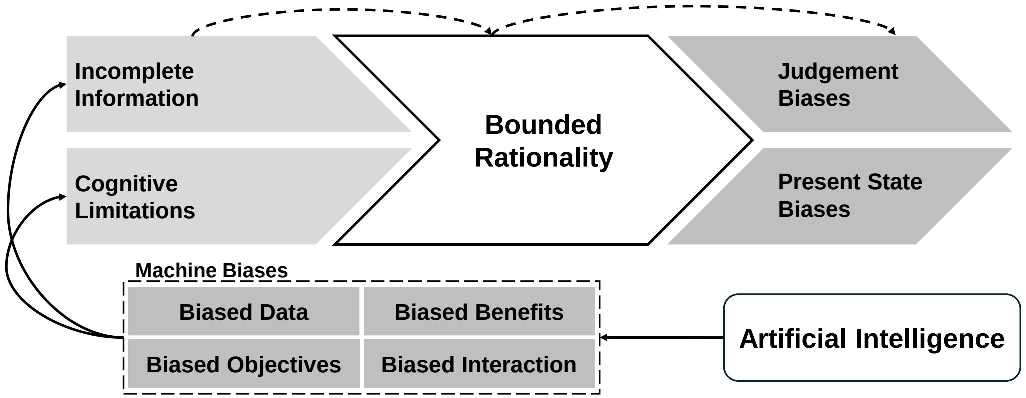
ML as a Method for Quantitative Data Analysis (after)

- **Descriptive statistics**
  - Moments of distributions
  - Correlations
  - Number summaries
  - Other
- **Machine learning**
  - Explainable ML (focus on hypothesis testing)
    - Parametric methods
    - Support vector machines
    - Random forest models
    - Neural nets
  - ML (focus on prediction)
    - Parametric methods
    - Non-parametric methods
    - Support vector machines
    - Random forest models
    - Neural nets

Focus in IB (after)

AI/ML also Affect International Business Theory

- We can make predictions about firm decisions, frequently because people have biases
- Large-scale AI applications may change these biases
- We can probably change our theoretical assumptions to incorporate these new biases, but we need to know which biases matter for which decision



Lindner, T., Puck, J., & Puhr, H. (2025). Artificial Intelligence in International Business: IB Theory under Augmented Decision-Making. Working Paper.

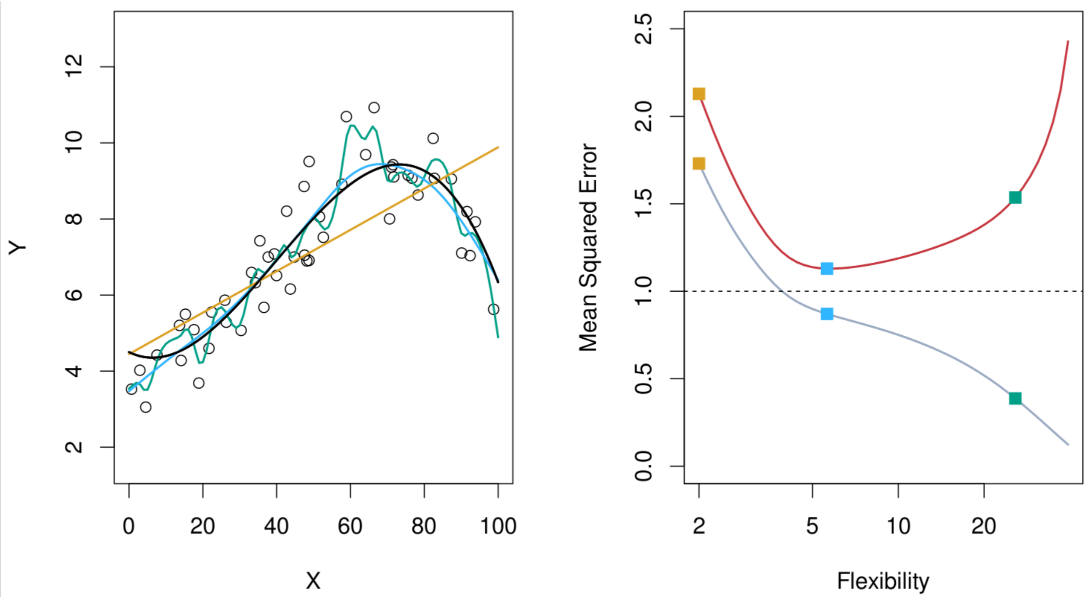
Research Applications of Big Data and AI in IB

Break

Conceptual Foundations of AI and Machine Learning

Train/Test Im Machine Learning models

- In ML, datasets are split into training and testing data (something like 60/40 or 70/30)
  - Models are built on the training data, then fit is assessed on the testing data (see figure below)
- In cross-validation, we do this repeatedly
  - K-fold cross-validation takes k splits of the data into train-test.



https://doi.org/10.1007/978-3-031-38747-0

Cross-Validation

- k-fold cross-validation
  - Split the training data into k groups („folds“)
  - Train the model on k-1 folds and test on the remaining fold
  - Repeat the process for each of the k folds
  - Average the model performance (e.g., MSE) over the k folds

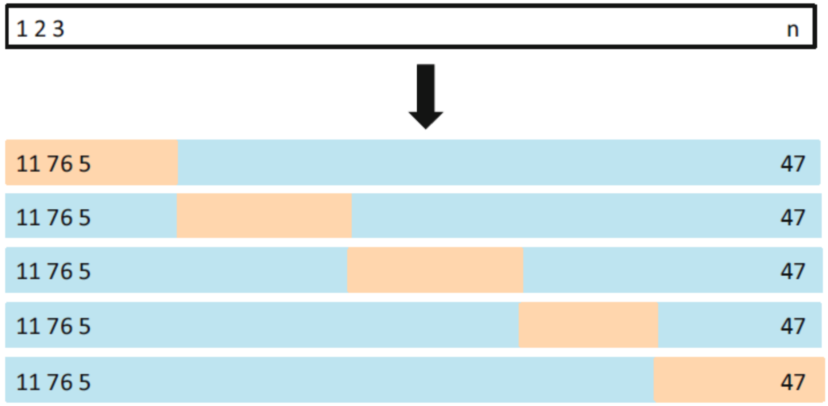
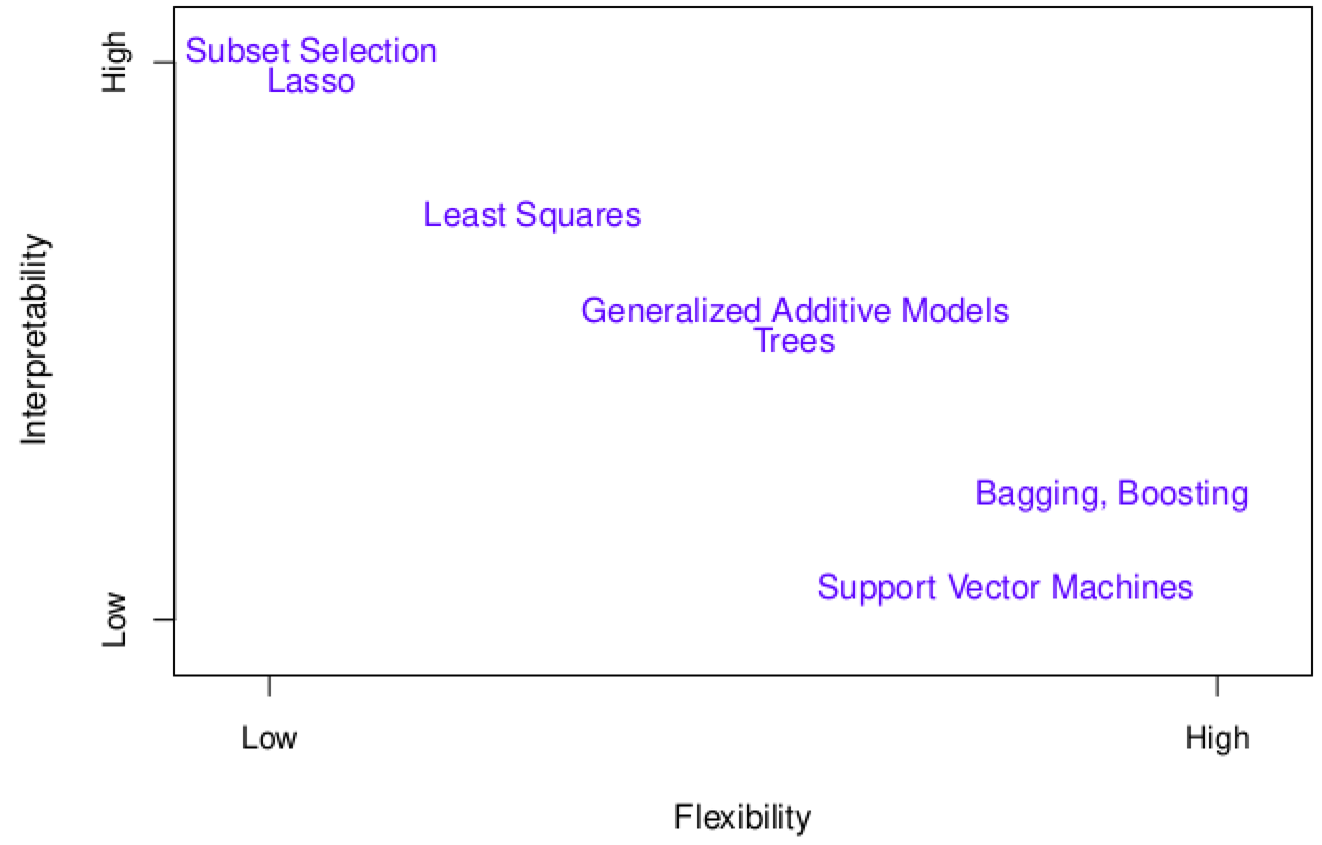


FIGURE 5.5. *A schematic display of 5-fold CV. A set of n observations is randomly split into five non-overlapping groups. Each of these fifths acts as a validation set (shown in beige), and the remainder as a training set (shown in blue). The test error is estimated by averaging the five resulting MSE estimates.*

https://doi.org/10.1007/978-3-031-38747-0

A variety of models with different flexibility and interpretability



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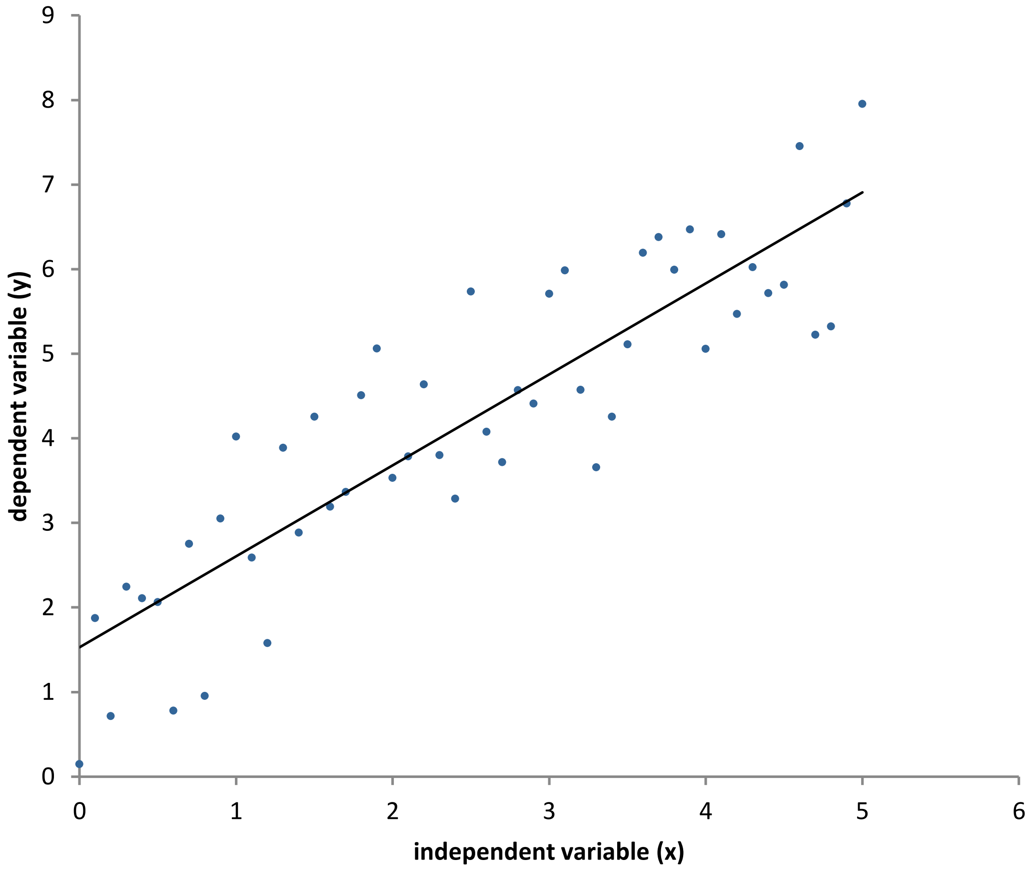
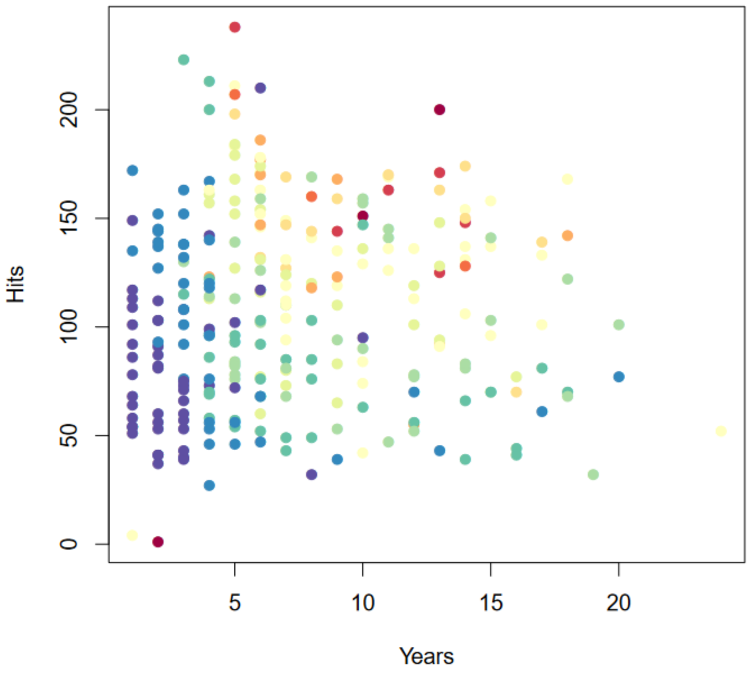
Least Squares: The Lest Intelligent AI

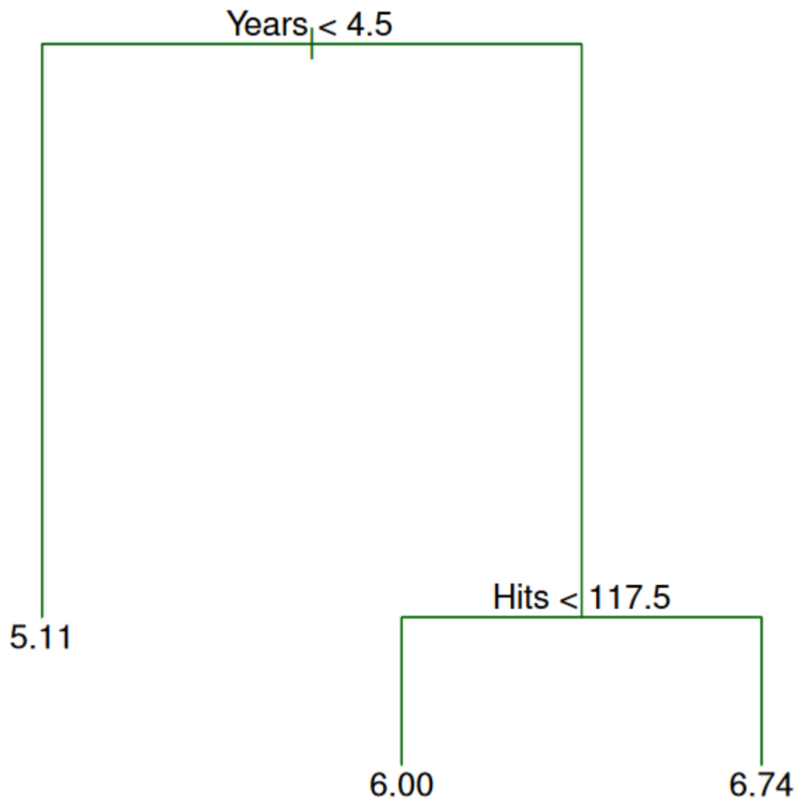


- In the simplest form, we want to understand how a variable y changes with a variable x
- Assumed functional form:
  - $y_i = b_0 + b_1 \cdot x_i + e_i$
- Learning problem:
  - Find b_0 and b_1 such that the squared sum of e_i is minimal.

Decision trees

- As the name suggests, decision trees are related to sequential decision-making problems





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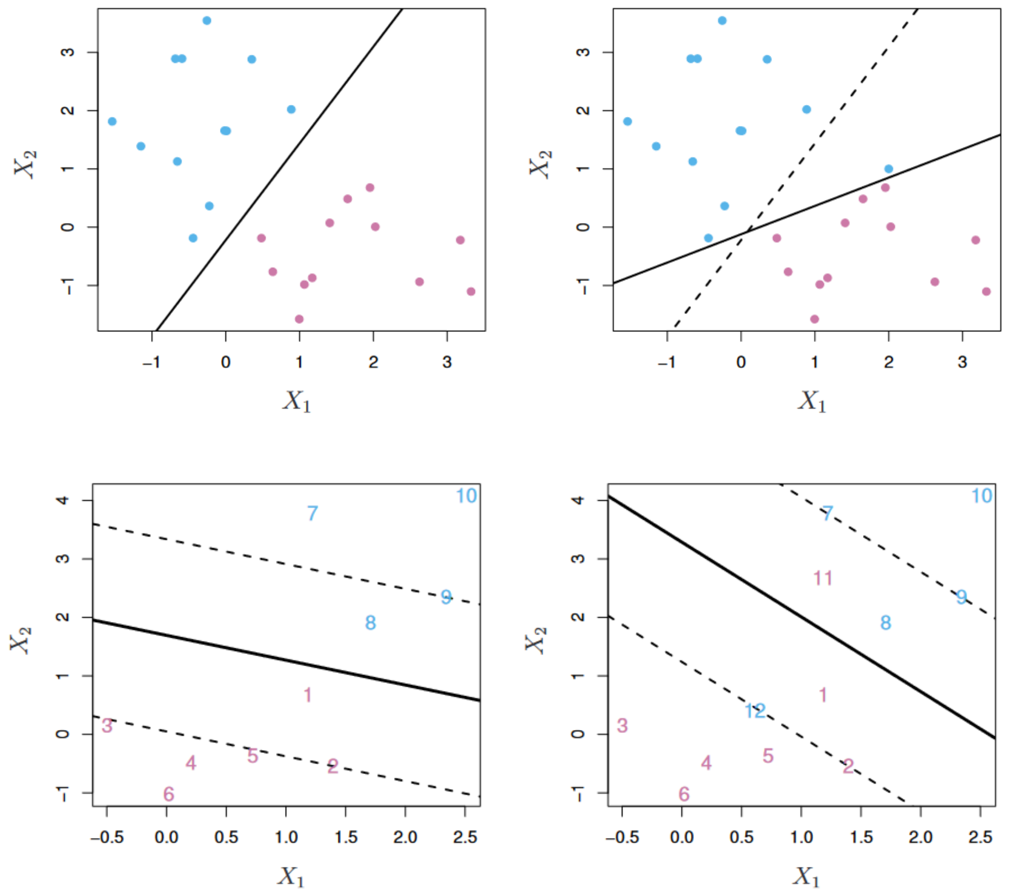
Random forests aggregate repeated runs of decision trees

- For aggregation, we draw random samples from the training data for repeated estimation of the decision tree
- In this approach (bagging), we reduce the variance in our prediction by re-running the training model on different subset
- To maximize predictive power, we de-correlate predictions, using a method analogous to the Mahalanobis correction

Support Vector Machines

- SVMs let us relax some rigid assumptions
- Support vectors let us introduce a soft boundary in classification problems
  - Noise in the data can give very different results
- If we allow for some error, we can get more consistent results
- In extensions, we can also use non-linear (and higher dimensional) separators

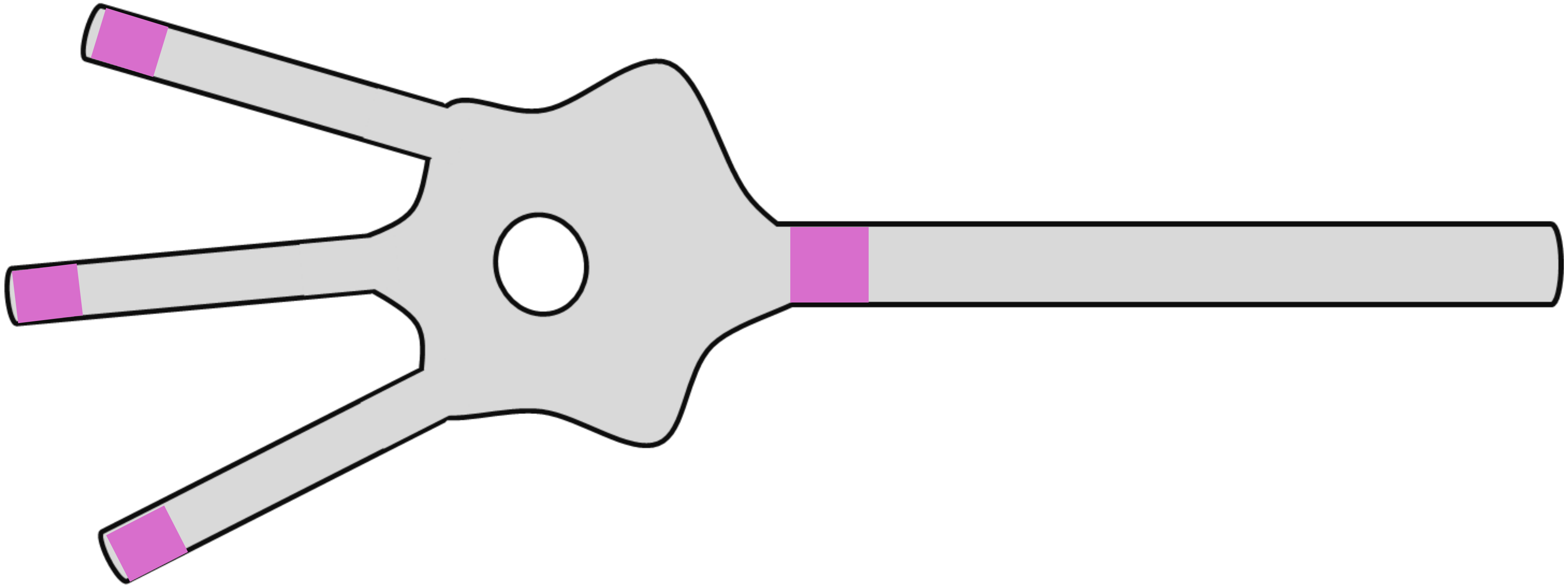


https://doi.org/10.1007/978-3-031-38747-0

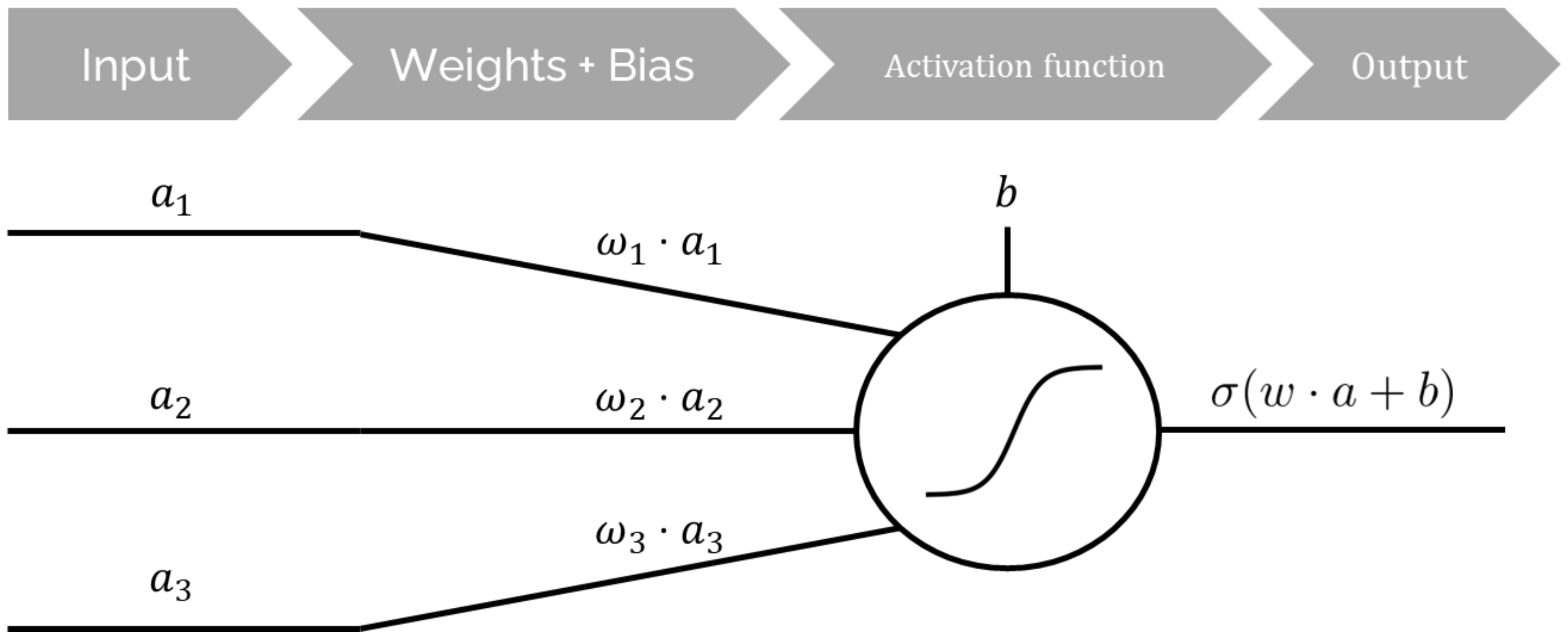
Deep Learning and Neural Nets

1. **Neurons and neural nets**
2. Learning
3. Progress

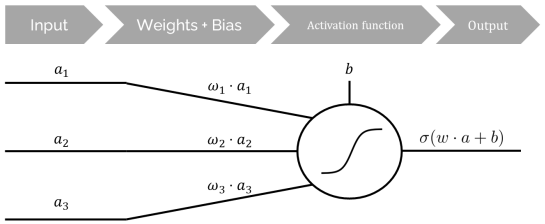
Biological Neuron

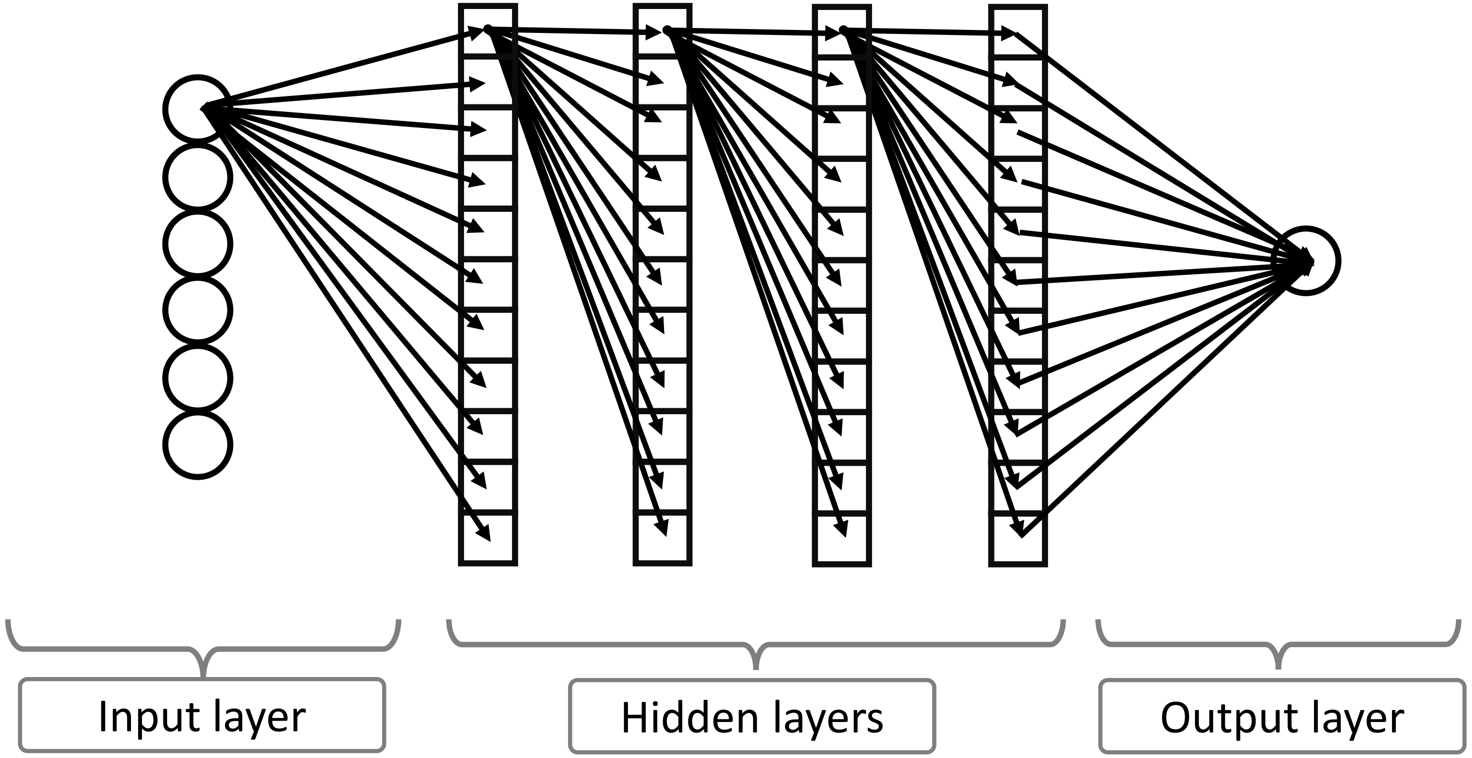


Artificial Neuron



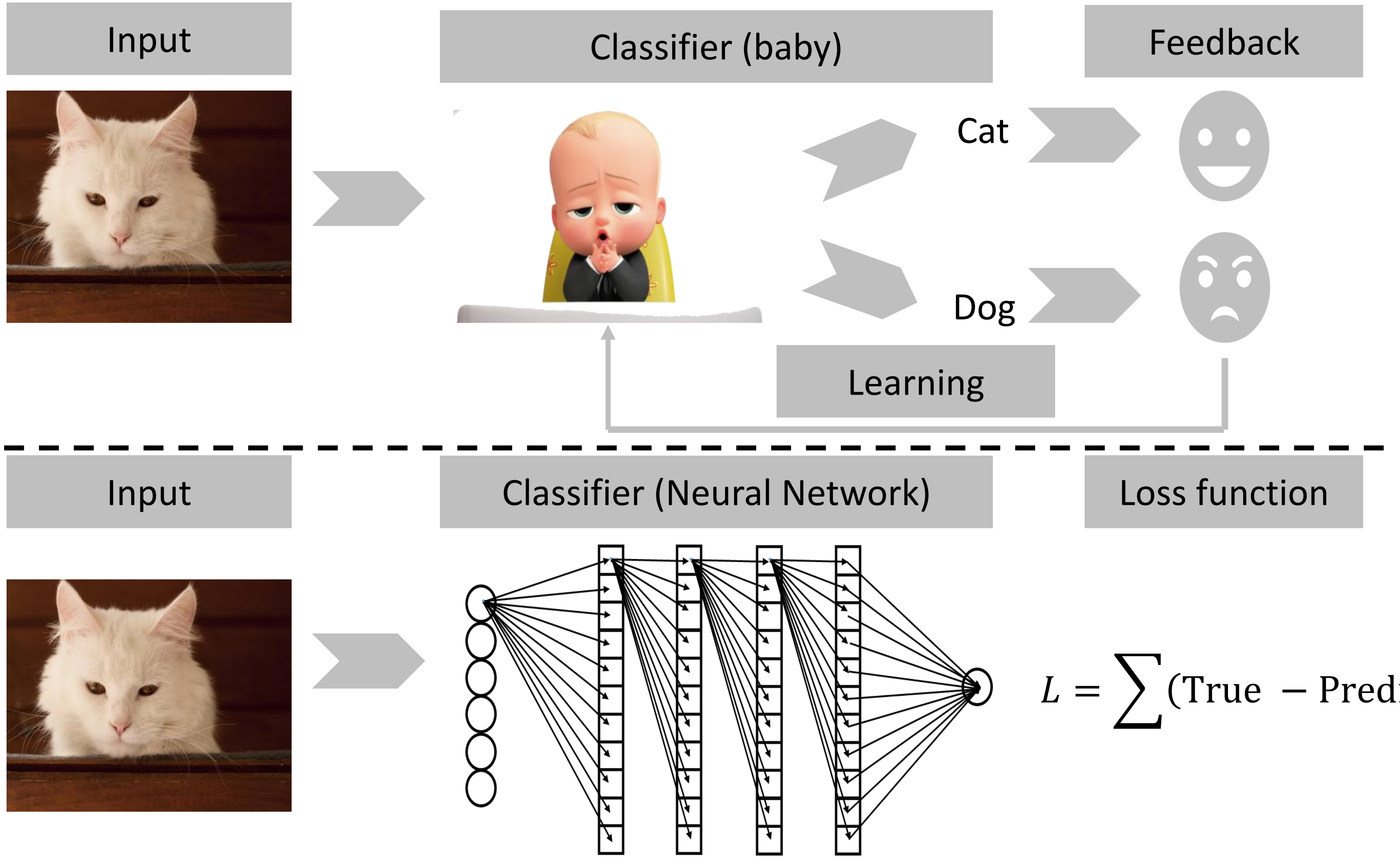
Artificial Neural Net





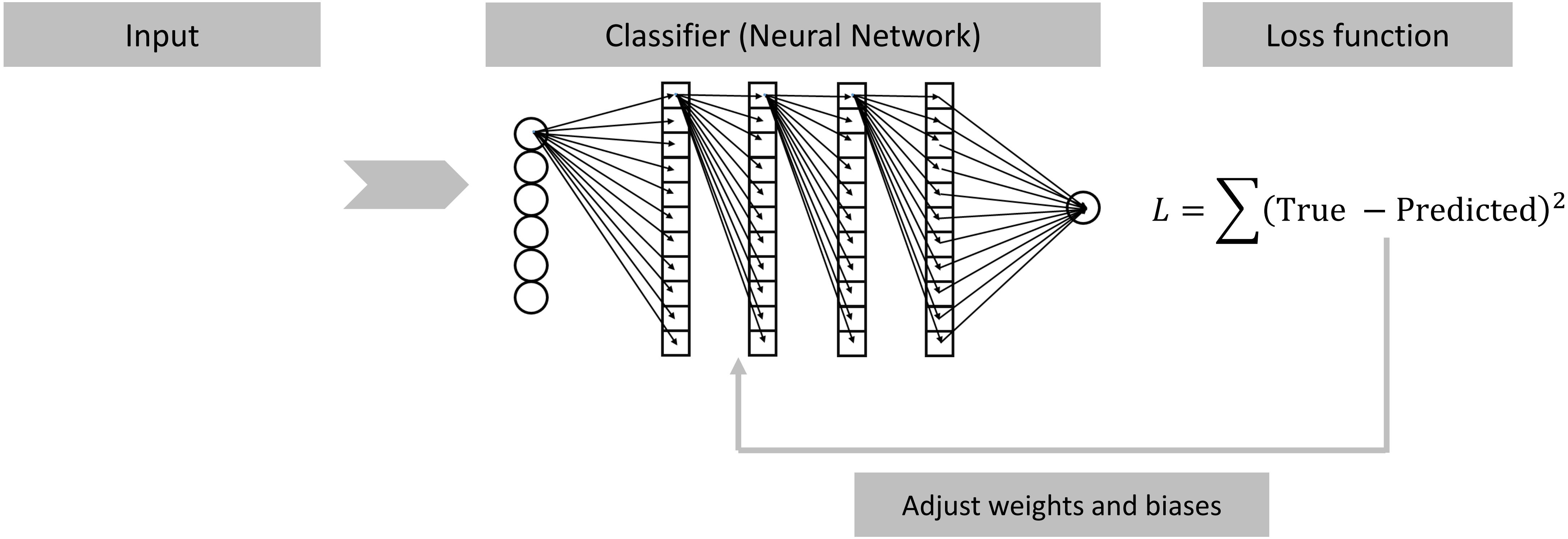
Deep Learning and Neural Nets

1. Neurons and neural nets
2. **Learning**
3. Progress



$$L = \sum (\text{True} - \text{Predicted})^2$$

Training a neural network

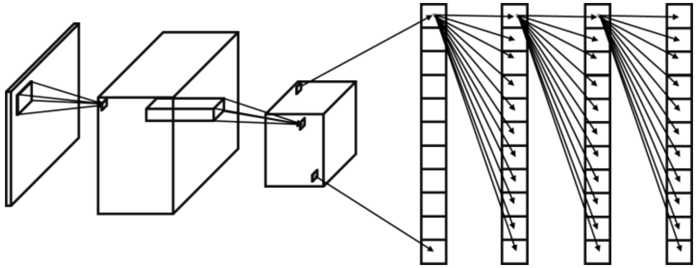


Deep Learning and Neural Nets

1. Neurons and neural nets
2. Learning
3. **Progress**

1997: Deep blue vs. Kasparov

2012: AlexNet (A. Krizhevsky et al.)



2016: AlphaGO vs. Lee Sedol (Google)

2022: Dall E 2 (OpenAI)

2022: Copilot (Github)

2022: ChatGPT (OpenAI)

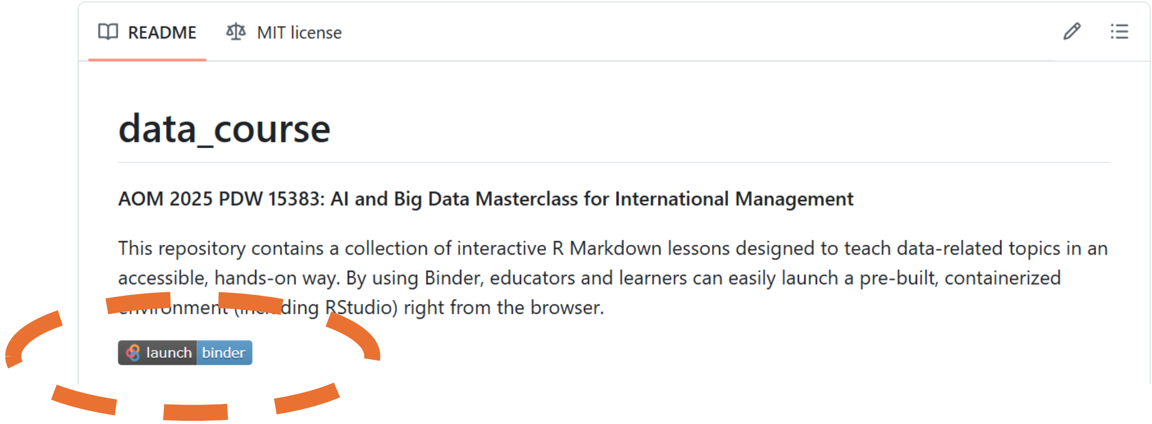
’Welcome to a world, where data is the new oil, and neural networks are the refineries that turn it into insights and predictions.’

by ChatGPT

A Basic Machine Learning Workflow in R

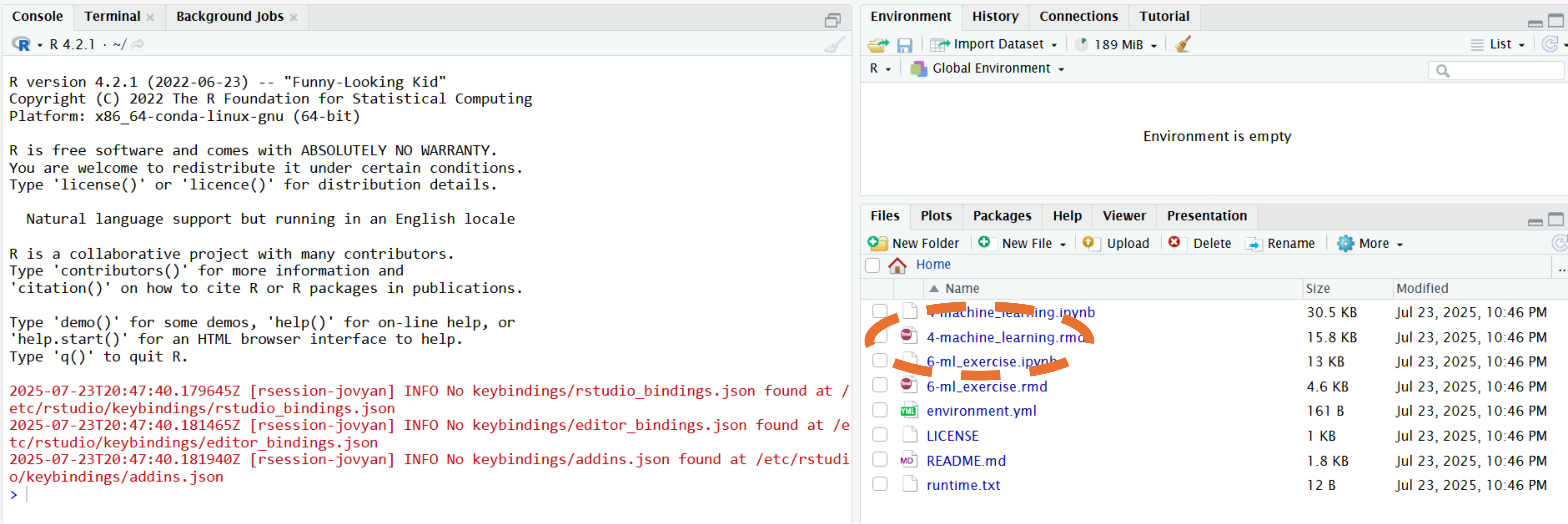
Hands-On Exercise

- Go to: https://tinyurl.com/3ub5famm
- Click on the „launch binder“ button
- This starts an RStudio session in your browser (takes 1-2 minutes)
- Let us know if there are issues



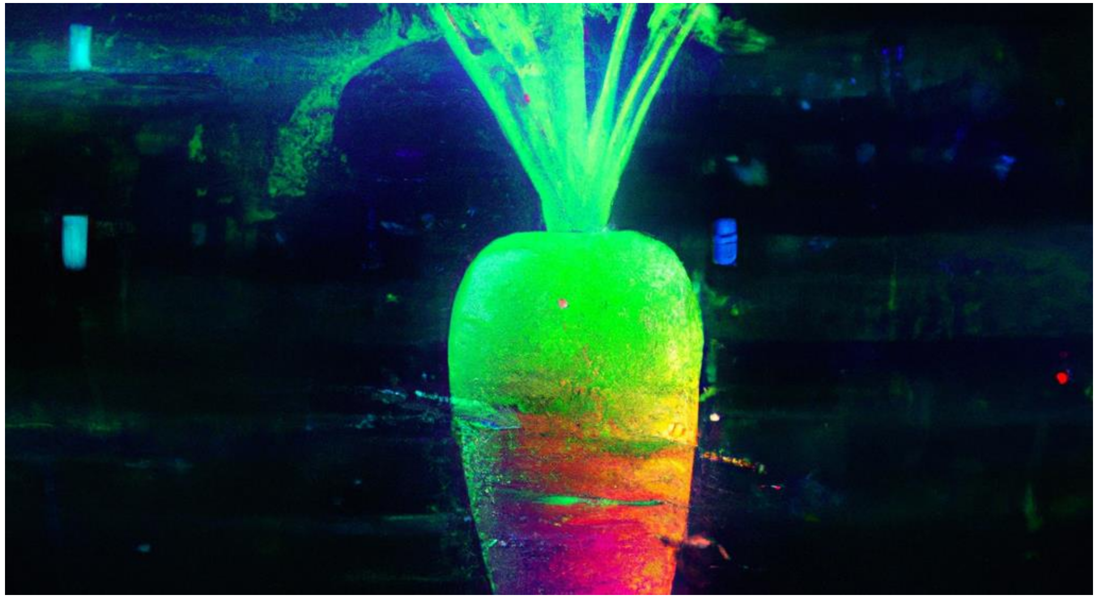
Hands-On Exercise

- Once the RStudio has opened, click on „4-machine_learning.rmd“ on the bottom right



Caret

- Caret is a library the builds a common interface for many machine learning algorithms from different libraries in r
- As the name suggests it is specialized for supervised learning (the outcome variable is known) so for **C**lassification **A**nd **Re**gression **T**asks.
- Many different types of algorithms
    - Trees & forests
    - Regressions
    - Support vector machines
    - Neural nets
    - Gradient boosting
    - …



The ML Workflow

Step I:
Preparing your data

- Formatting
- Test-Train split
- Preprocessing

Step II:
Training a learning algorithm

- Algorithm selection
- Validation
- Tuning
- Testing

Step III:
Building a learning architecture

- Model lists
- Ensemble models
- Auto-ML

Workflow for management research (very similar):

Choudhury P, Allen RT, Endres MG. 2021. Machine learning for pattern discovery in management research. *Strategic Management Journal* **42**(1): 30–57.

Step I: Preparing your data

- To prepare our data for machine learning we need to:
  - Make sure it is the right format
  - Split it into training and test data
  - Conduct necessary pre-processing steps

Preparing your data I

- The right format
  - Data comes in many formats
  - Not all are equally easy to process
  - Continuous numeric data is the easiest
  - Rank data is also okay (*)
  - Categorical data needs to be transformed into dummy variables
  - Text and images (videos) have their own approaches and will not be covered here

Preparing your data II

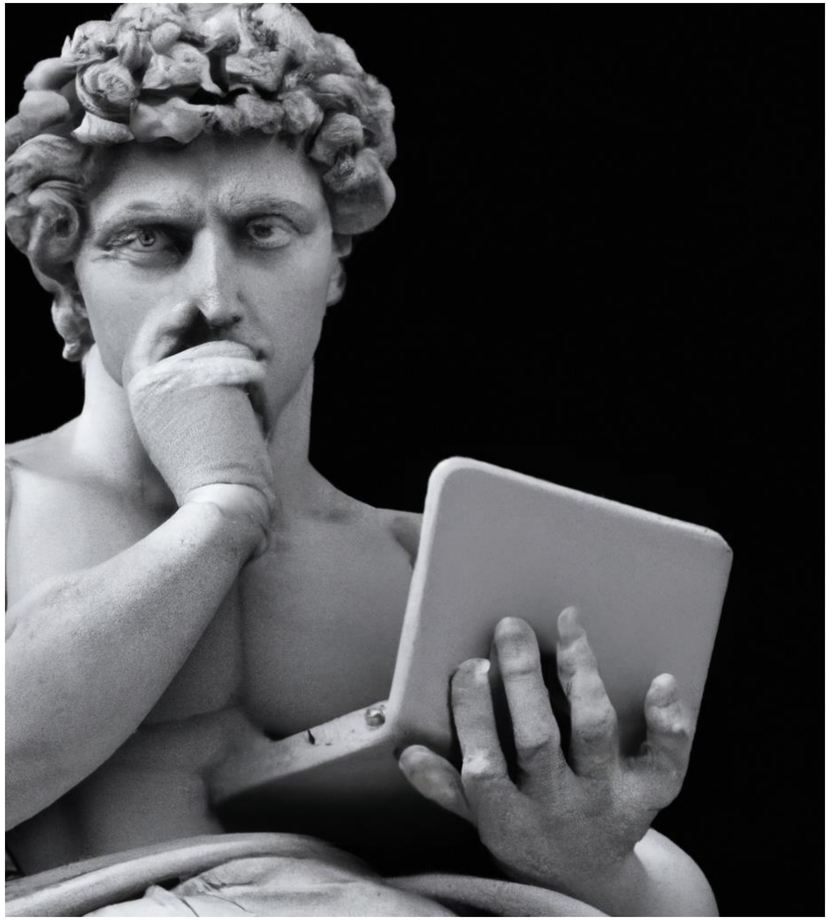
- To assess the fit of our models we need to split our data into a Test and a Training set
    - This is done because ML algorithms are prone to overfitting to the data
    - The performance on a data set the algorithm has not “seen” is more indicative of real world performance
    - In the real world the train-test split is often around 80:20-95:5 depending on how much data you have
    - When creating a train-test split we need to make sure that those datasets are sufficiently similar
    - We accomplish this by holding the distribution of the outcome variables as close to the initial distribution as possible

Preparing your data III

- Information content
  - Sometimes variables contain little or no variance (e.g., most/all customers come from the same country)
  - These variables contain little or no information but cost compute and could lead to overfitting
- Correlation
  - Some data points might be highly correlated
  - These variables contain redundant information and therefore, cost compute and might “confuse” models
- Imputation
  - Some variables might not be complete but still contain valuable information
  - We don’t want to drop observations or these variables -> imputation
- Centering and scaling
  - For some algorithms it can be useful if the variables are centered and scaled (e.g. clustering)

Preparing your data IV

- Things that can go wrong during data prep
  - Technical stuff
  - Wrong order: Sometimes it is tempting to preprocess all the data and then splitting it.
  - This is ok as long as the preprocessing does not involve looking at the whole dataset (as for example with imputation and correlation tests)
  - As a general rule:
    - Changing the format is ok (e.g., creating dummies)
    - Computing something is not (imputation, scaling, …)



Step II: Training a Learning Algorithm

- To train a machine learning algorithm we need to:
  - Select (an) appropriate algorithm(s)
  - Select a way to validate our algorithm to avoid overfitting
  - Tune the algorithm’s hyper-parameters to find the best learner
  - Test the out-of-sample (OOS) performance of our trained algorithm

Training a Learning Algorithm I

- Choosing the right algorithms for a problem is as much art as it is science. Some important classes of algorithms include:
  - https://topepo.github.io/caret/available-models.htmlt
  - Decision tree based
  - Linear models
  - Neural networks
- Experience shows that many weak predictors can be combined to create strong predictors. Those ideas are key to:
  - Boosting
  - Bagging
  - (“StatQuest with Josh Starmer” on YouTube for intuitive explanations)

Training a Learning Algorithm II

- ML algorithms are very prone to overfitting.
- This is why we use validation during the training process to find the parameter tuning which optimize OOS accuracy
- Common methods are cross validation and bootstrapping:
  - CV: We split our data into k-Folds and train the model on k-1 of them. Then we estimate OOS performance on the remaining fold. We do this on all k combinations.
  - Bootstrapping: here we draw observations form the existing data set with repetition and test performance on the original dataset
  - Time series sometimes need other methods

Training a Learning Algorithm III

- ML algorithms try to fit the model parameters to the data.
- But the models themselves have (hyper-) parameters which determine how well they can “learn” from the data.
- There are different approaches to hyper parameter tuning:
    - Grid search
    - Random search
    - Adaptive resampling
    - Others (not yet implemented in caret; e.g. evolutionary algorithms in the “mlr” package)

Training a Learning Algorithm IV

- AFTER building our models we can test and compare their performance on the test data.
- Theoretically, test data is “burnt” once we check a models OOS performance on it. If we engage in further optimization, we start to (implicitly) fit to the test data.
- This is not very practical. Rule of thumb: Don’t do statistics to the test data performance. Comparing 10 models is probably ok, 1000 is not.

Step III: Building a Learning Architecture

- Model lists allow us to train multiple models at the same time with just a single line of code
- Auto-ML (e.g., in H2O)
- Ensemble models
  - Many weak learners can together create a strong learner
  - Simple approaches use averages or votes to aggregate the results of multiple instantiations of the same algorithm
  - But we can also use different algorithms
  - And use ML-algorithms to find the best way to combine them
  - “It’s turtles all the way down” – Hawking S. 1988. *A brief history of time.*

Other Resources

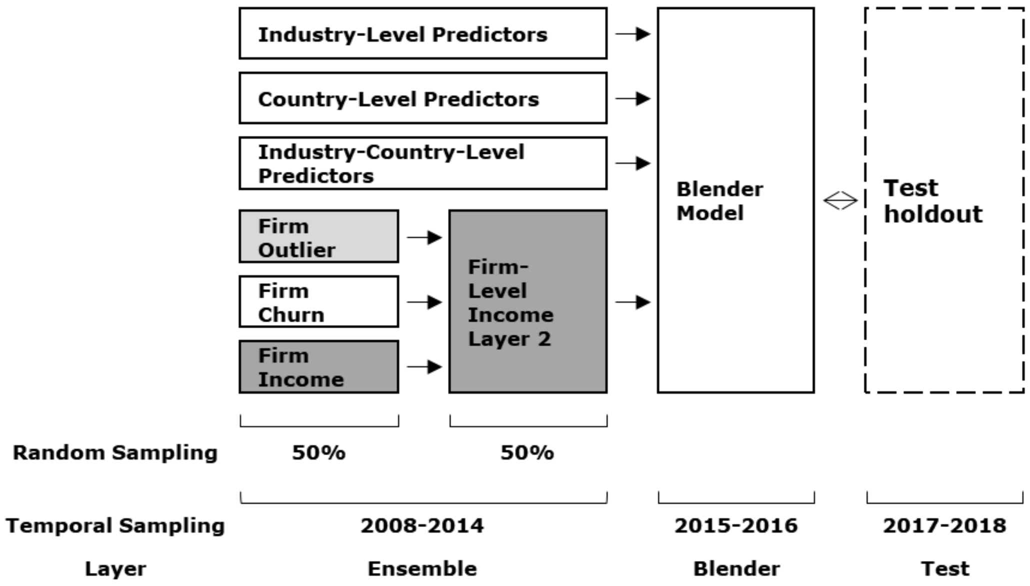
- DataCamp
- YouTube
- Caret documentation
- Other ML libraries for R
  - mlr
  - H2O
- ChatGPT et al.

Case Study: Predicting Foreign Subsidiary Profits

Forecasting Austria's International GDP with ML Techniques

- **Goal:** Explore the applicability of machine learning techniques to GDP forecasting utilizing firm-level micro data
- Approach
  - Ensemble model of 60 ML-algorithms
  - Utilizing information embedded on different scales of the data (firm-level, country-level, industry-level,…)
  - Special attention to outlier prediction
- Data
  - OENB Active Direct Investments
  - OECD Composite Leading Indicator

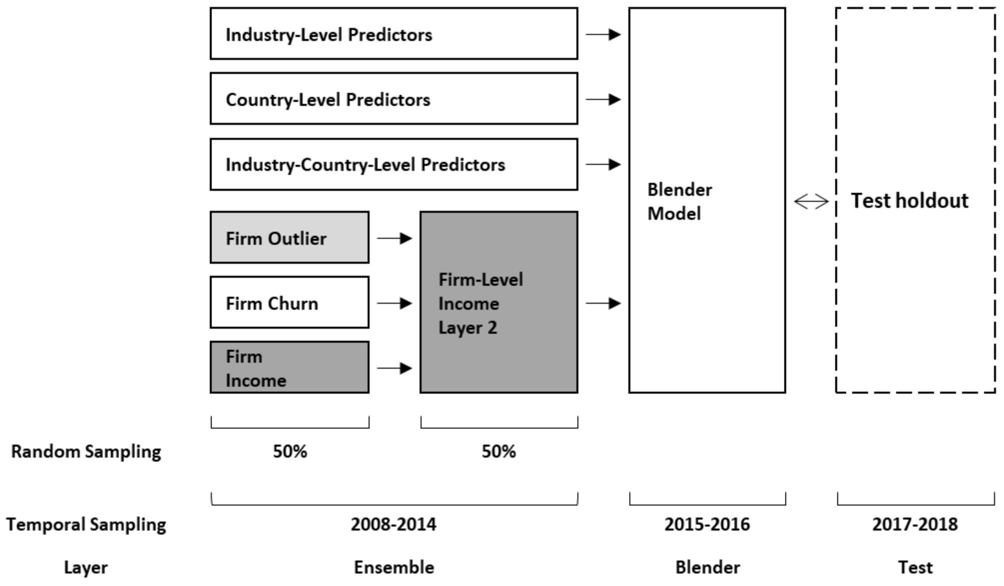
Simplified model and data sampling framework



Characteristics of the Data Shape the Training Architecture

- Two important characteristics
  - Several information rich scales/ levels (firm, country-industry, country, industry)
  - Short time series
- To account for both we implemented
  - two **layered firm level sub ensemble** allowing the estimation of firm level characteristics, based on traditional observation bases random sample splits
  - A single layered architecture for the **aggregate models** accounting for the time series nature of the data

Simplified model and data sampling framework



New Features Reflect the Information Found at Different Scales

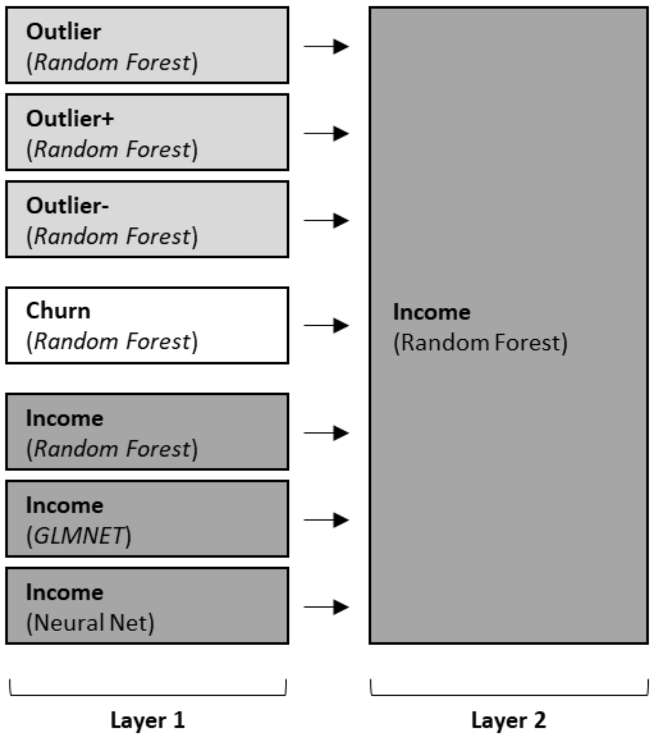
- Firm Level Features
  - Year of entry
  - Year of exit (churn)
  - Outlier scores:
    - Isolation score (tree based)
    - Local outlier factor (clustering/density based)
    - Top/bottom Quantile
- Temporal Features
  - All data points were lagged by up to 6 years to cover temporal effects

- Aggregation Level Features
  - Aggregation Levels:
    - Industry – Country
    - Industry
    - Country
  - Features (absolute & relative):
    - Income
    - Churn
    - Entry
    - Number of firms

Firm Level Ensemble Architecture

- Outlier prediction
  - Random forests predict (some of the) outlier features
- Churn
  - A random forest predicts the exit (/churn) feature
- Income
  - Income is used as the label in training of a random forest, a GLMNET and a neural net model.
- Layer 2
  - Layer 2 predicts income with a random forest, but also takes the predictions of the previous models as input

Firm Level Ensemble Model



Aggregate Level Ensemble Architecture

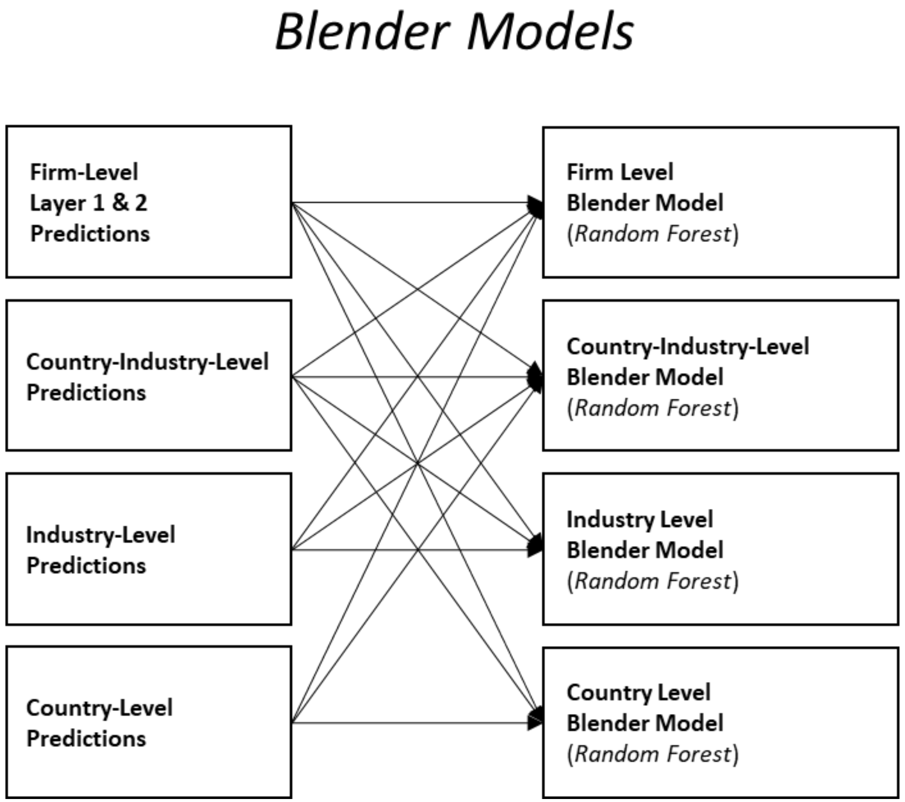
- Aggregation levels
  - Industry-Country Years
  - Industry-Years
  - Country-Years
- Predicted Labels
  - Income
  - Number of firms, entries, & exits
- Models
  - A gradient boosted tree and linear model each
- Key issues
  - Low number of observation in country and industry aggregates

Aggregate Level Ensemble Models

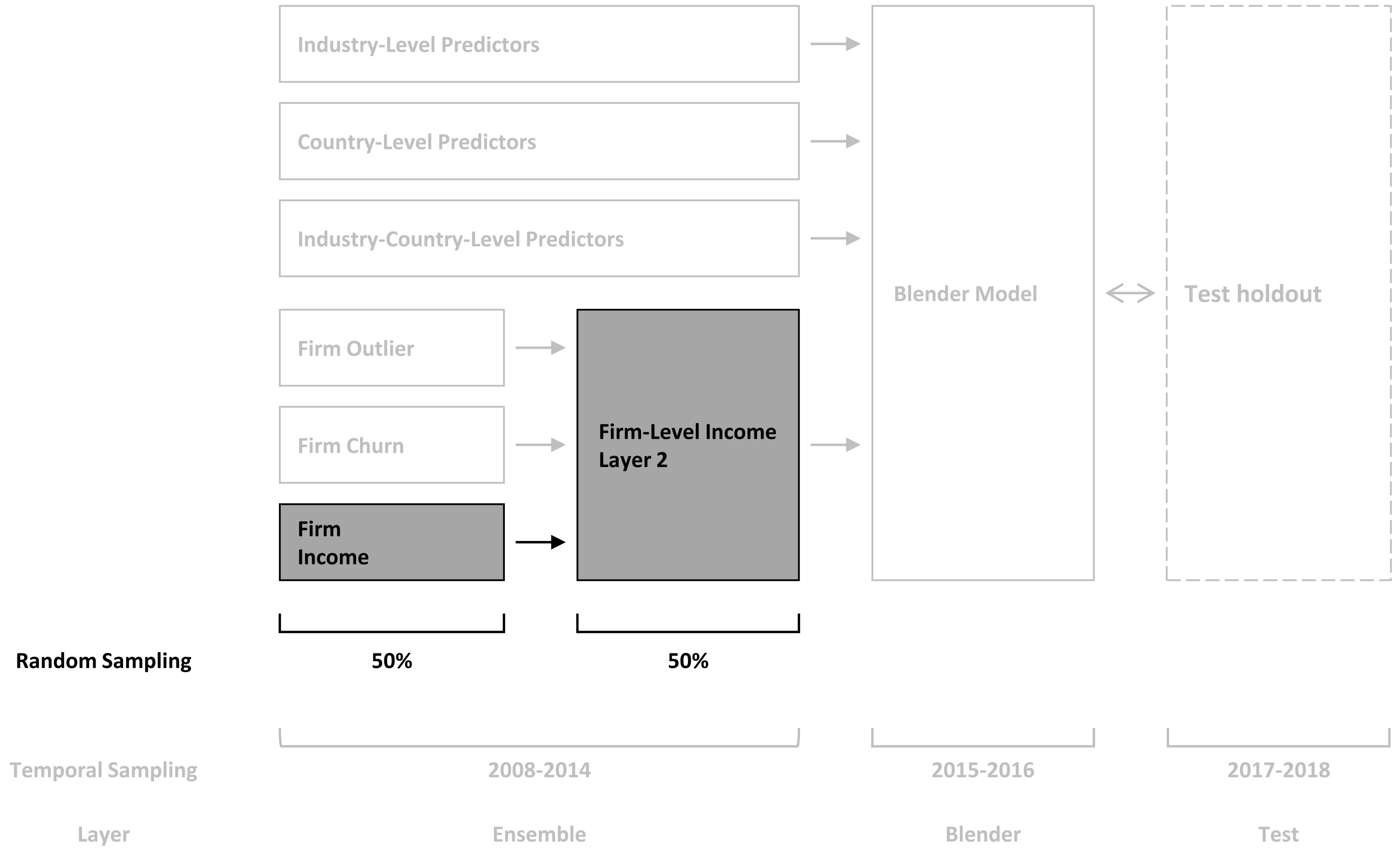
	Gradient boosted tree	Gradient boosted LM
Number	**Total Income** (*Gradient boosted tree*)	**Total Income** (*Gradient boosted linear model*)
	# of Entry (*Gradient boosted tree*)	**# of Entry** (*Gradient boosted linear model*)
	# of Churn (*Gradient boosted tree*)	**# of Churn** (*Gradient boosted linear model*)
	# of Firms (*Gradient boosted tree*)	**# of Firms** (*Gradient boosted linear model*)
Growth	**Income Growth (%)** (*Gradient boosted tree*)	**# of Income Growth (%)** (*Gradient boosted linear model*)
	# of Entry Growth (%) (*Gradient boosted tree*)	**# of Entry Growth (%)** (*Gradient boosted linear model*)
	# of Churn Growth (%) (*Gradient boosted tree*)	**# of Churn Growth (%)** (*Gradient boosted linear model*)
	# of Firms Growth (%) (*Gradient boosted tree*)	**# of Firms Growth (%)** (*Gradient boosted linear model*)

Blender Models

- Aggregation levels
  - Firm
  - Industry-Country Years
  - Industry-Years
  - Country-Years
- Predictors
  - Previous years income
  - Predictions of all the models
  - Country and industry level predictions can not be combined

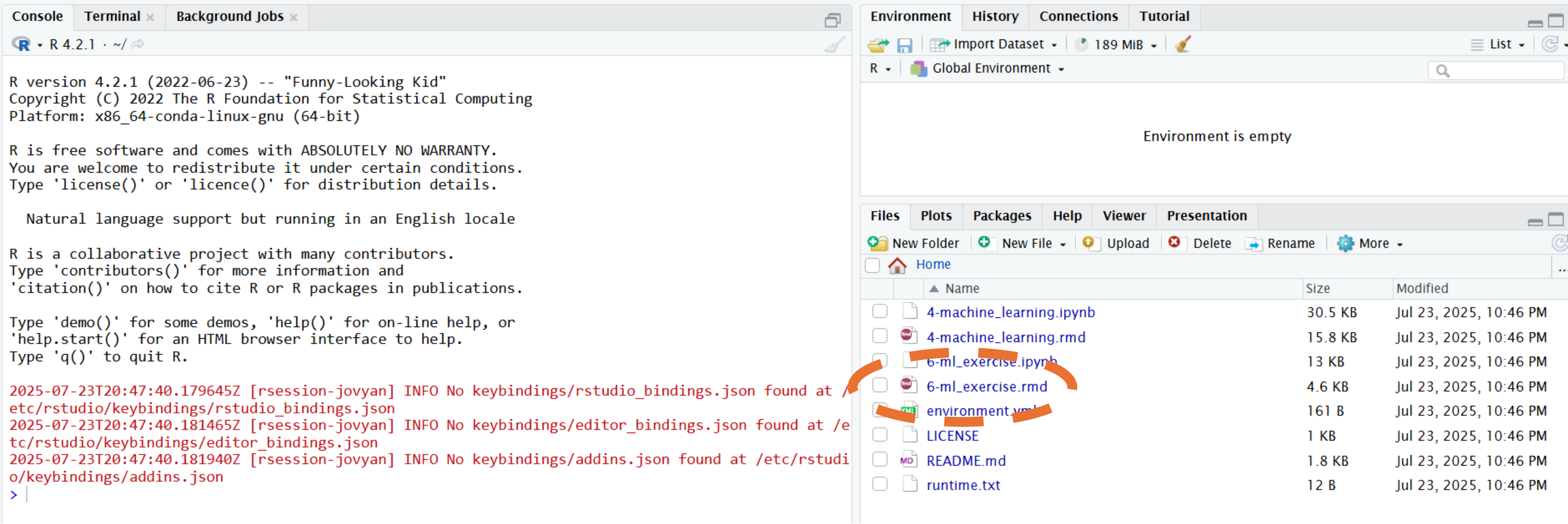


Your Turn!


Industry-Level Predictors
Country-Level Predictors
Industry-Country-Level Predictors
Firm Outlier
Firm Churn
Firm
Income
Firm-Level Income
Layer 2
Blender Model
Test holdout
Random Sampling
50%
50%
Temporal Sampling
2008-2014
2015-2016
2017-2018
Layer
Ensemble
Blender
Test

Hands-On Exercise

- Once the RStudio session has opened, click on „6-ml_exercise.rmd“ on the bottom right



Coffee House Style Discussion