



# Text Analysis for Social Sciences in Python

## Week 7: Text as Data – Supervised Methods & Model Evaluation

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WINTER SEMESTER 21/22

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# Last week...

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PCA vs. PLS in Scikit-learn

Has anyone given a try yet at the bonus exercise?

...any questions with the materials?

# Consultation Slots for Wednesday 01.12

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<https://docs.google.com/spreadsheets/d/1E-IFBNDNk7-5GxALoYRfK-P8G05aYJ8v9j0uEjUsZ5M/edit?usp=sharing>

Slight schedule change (starting @ 8AM) – please check again your assigned schedule!

# Today's agenda

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## 1. Supervised ML methods

- (Regression) Linear, Lasso vs. Ridge regression
- (Classification) Random Forest, Decision Tree vs. K-nearest Neighbor vs. Support Vector Machines

## 2. Model Evaluation

- Classification Accuracy
- Logarithmic Loss
- Confusion Matrix
- F1 score
- Mean Absolute Error (MAE) vs. Mean Square Error (MSE)

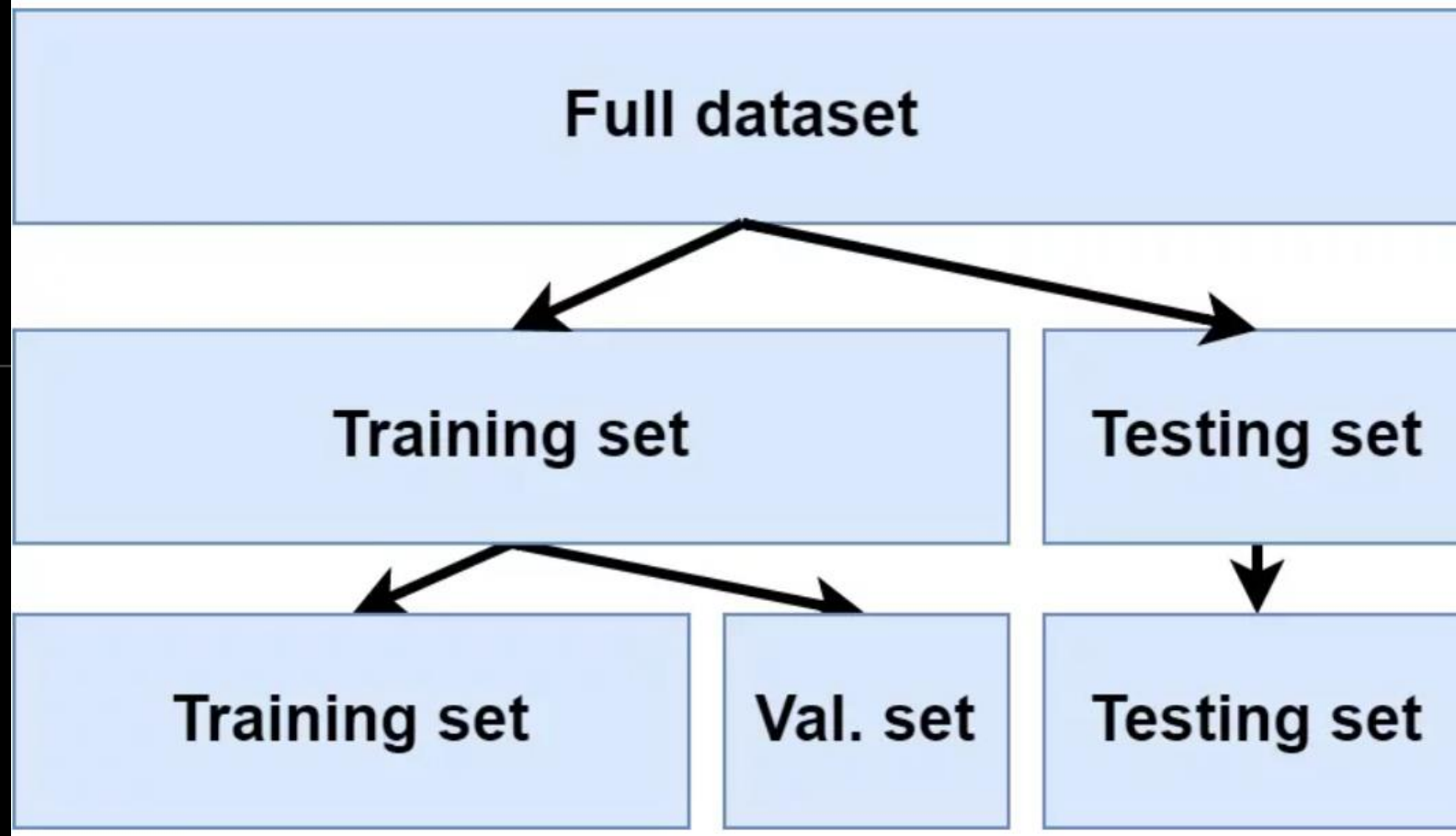
# Overview – Supervised algorithms

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Supervised learning algorithms are used when the training data has **output** variables corresponding to the **input** variables.

The algorithm analyses the input data, learns a function to map the relationship between the input and output variables.

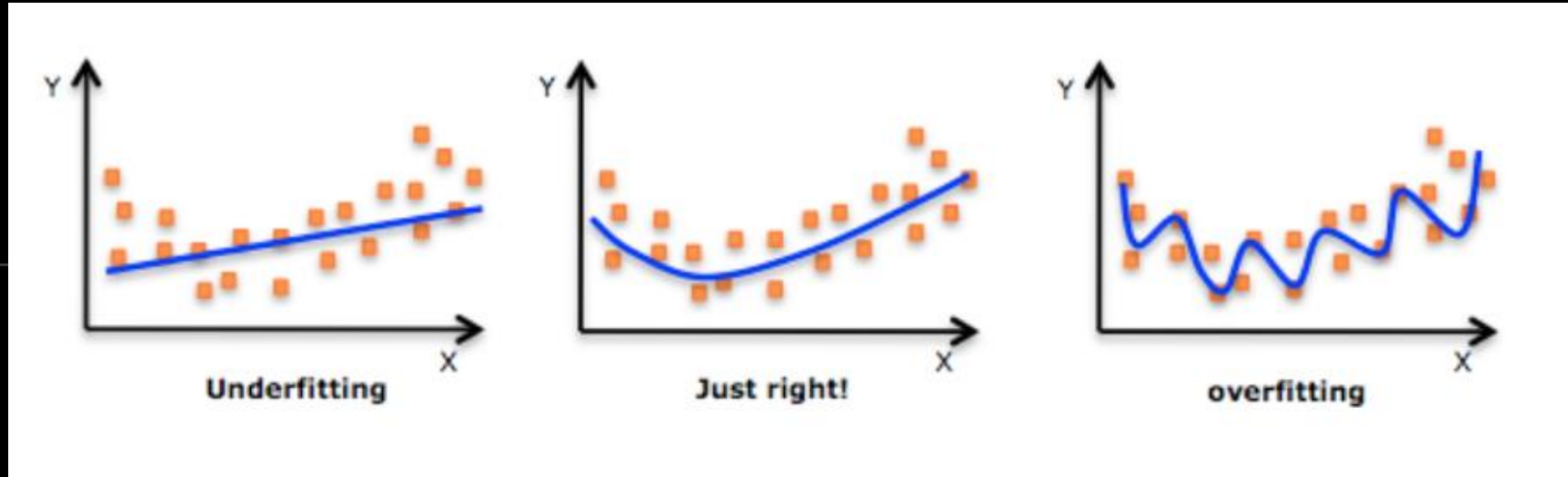
Supervised learning can further be classified into **Regression**, **Classification**, **Forecasting**, and **Anomaly Detection** (we focus on the former two in our course).



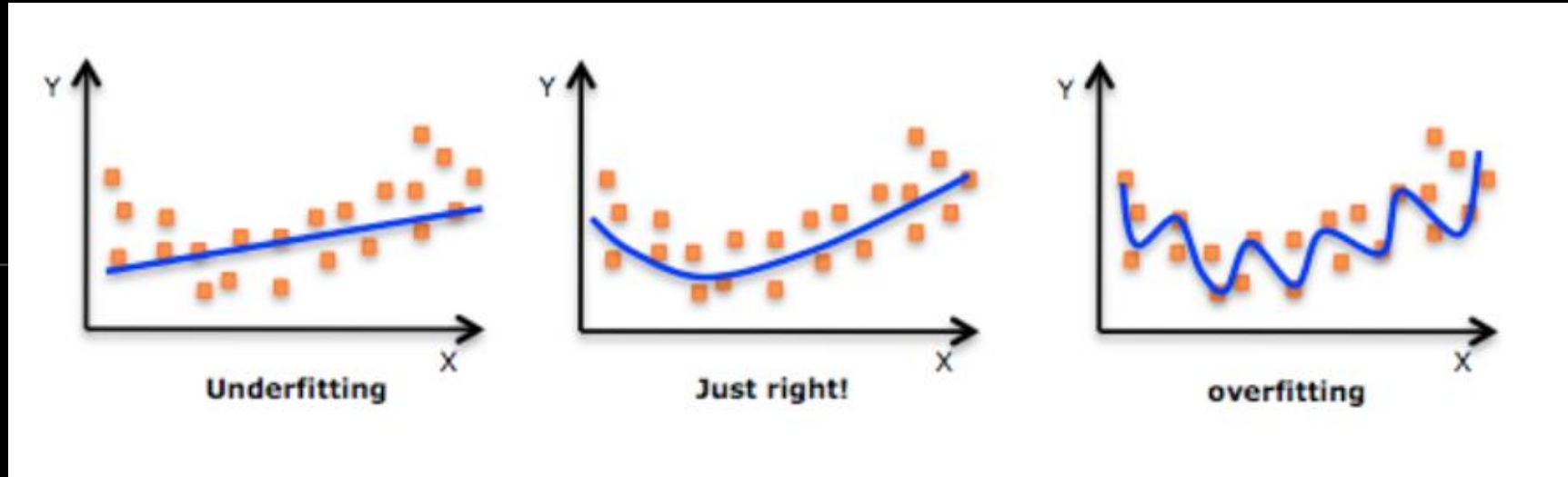
Every machine learning problem is an optimization problem.

→ Goal: find either a maximum or a minimum of a specific function.

→ The function that you want to optimize is usually called the loss function (or cost function).



How to balance the tradeoff between overfitting and underfitting a model?



How to balance the tradeoff between overfitting and underfitting a model?

→ Regularized regression



# 1.1 Regression Techniques

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Pre-requisite: The value you want to predict is CONTINUOUS.

Key idea: These techniques adds additional information to shrink parameter values of models → induce a penalty against complexity

$$\hat{y}_i = w_0 + \sum_{j=1}^m \beta_j X_{ij}$$

Lasso:  $J(\beta) = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^m |\beta_j|^2$

Ridge:  $J(\beta) = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^m |\beta_j|$

# 1.1 Regression Techniques (cont)

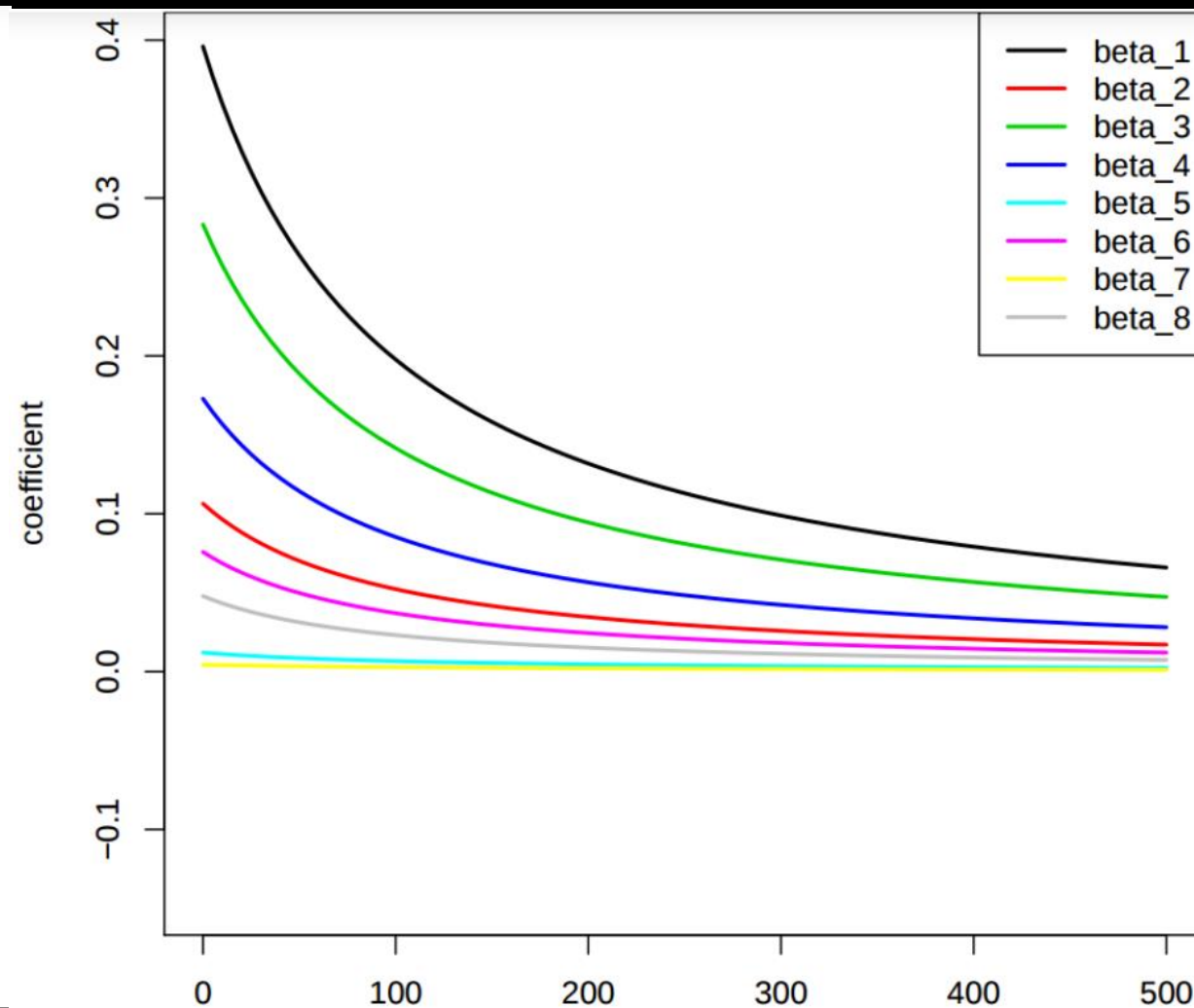
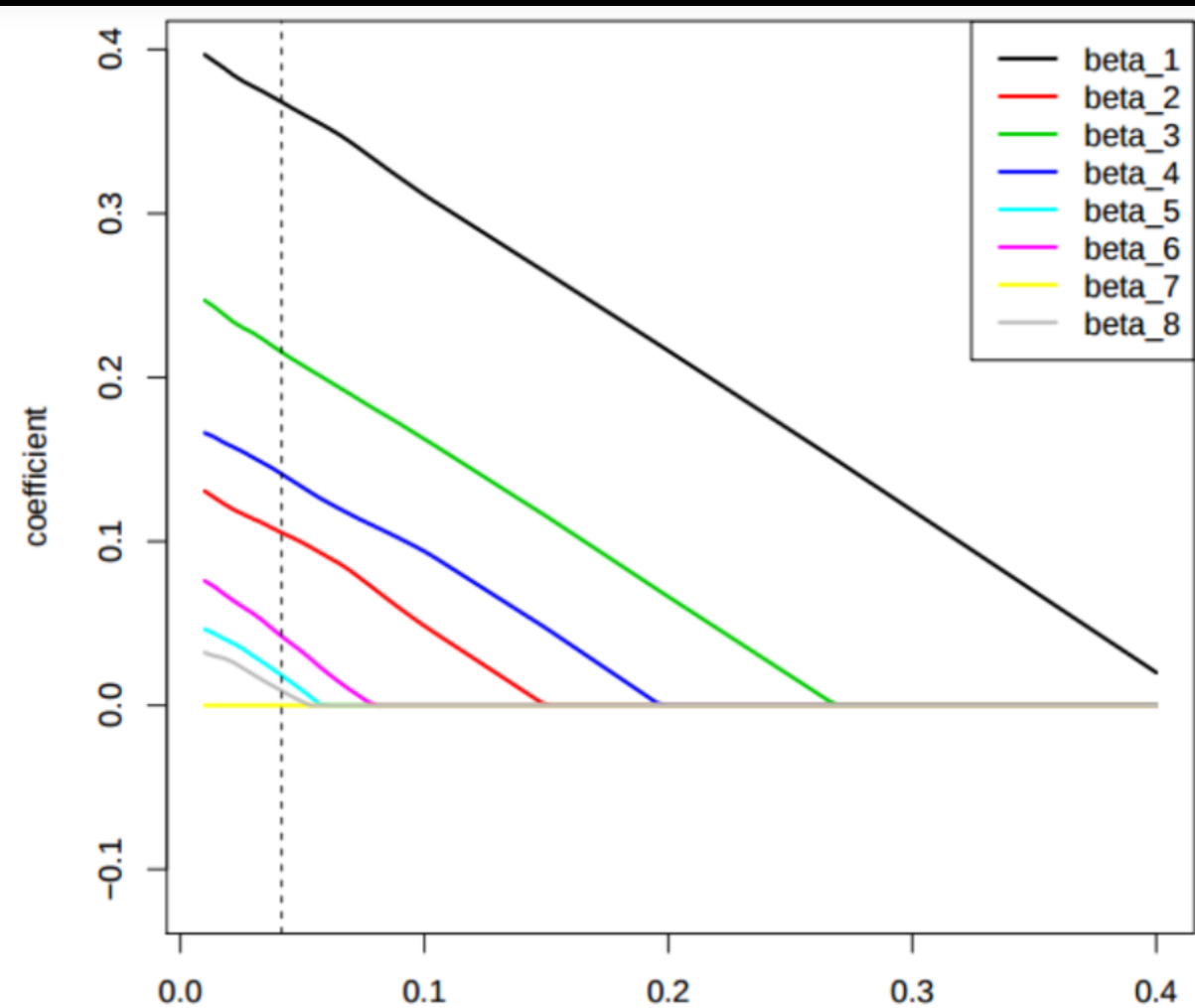
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→ Both methods “punish” the loss function for high values of coefficients  $\beta$ ,  
BUT...

**Lasso** kicks out variables with 0 coefficients (i.e. irrelevant features)

**Ridge** only minimize the impact of irrelevant features on the trained model, and does NOT kick them out.

# Lambda plots: Lasso vs. Ridge



# 1.2 Classification Techniques

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Pre-requisite: The value you want to predict is DISCRETE.

Key idea: Ensemble learning methods (i.e. combine predictions from multiple ML algorithms)

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# 1.2 Classification Techniques

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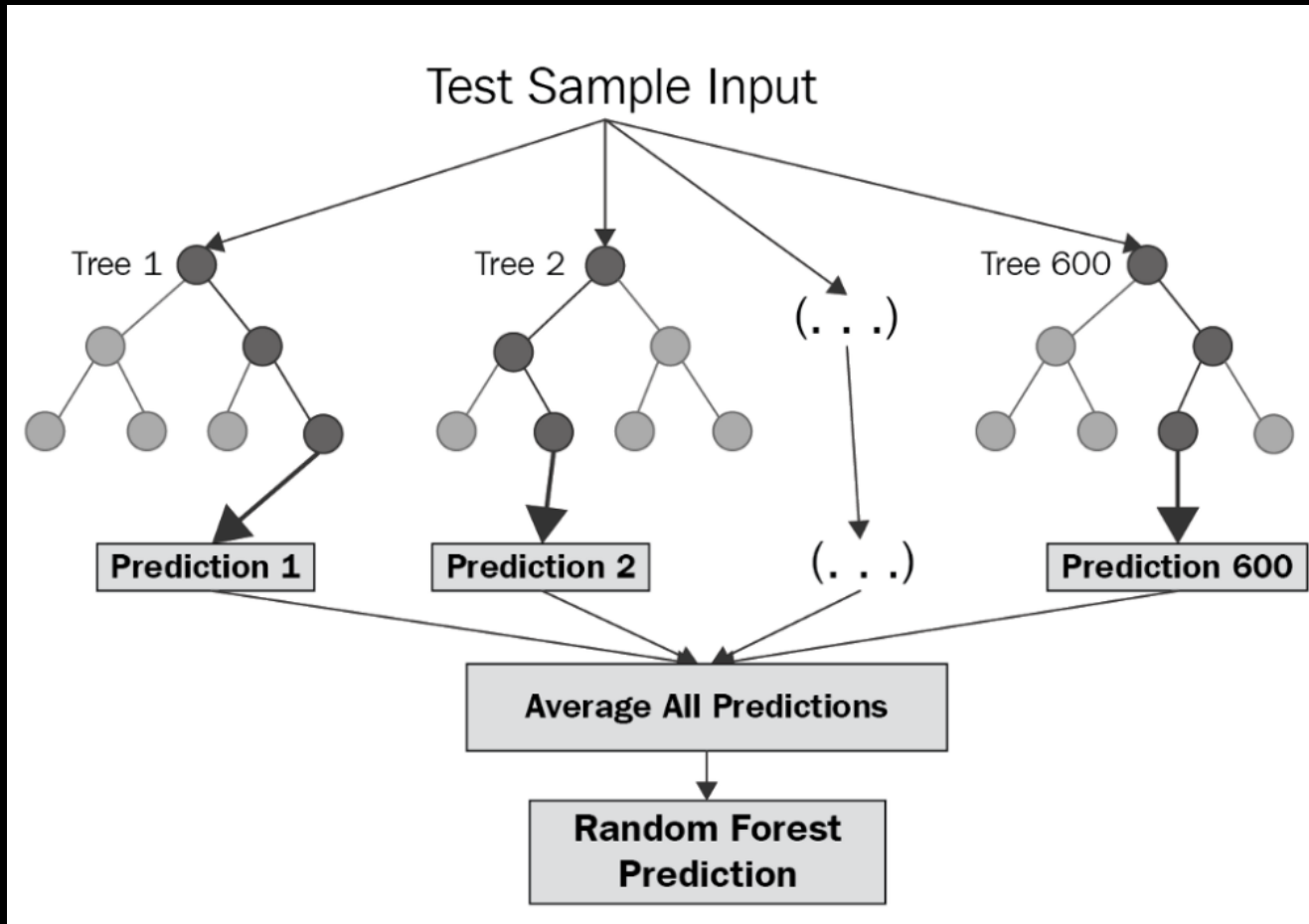
Pre-requisite: The value you want to predict is DISCRETE.

Key idea: Ensemble learning methods (i.e. combine predictions from multiple ML algorithms)

- Boosting = algorithms that utilize weighted averages to make weak learners into stronger learners → Each model runs, dictates what features the next model will focus on.
- Bagging = Each model run independently (by random sampling with replacement i.e. bootstrapping), and then aggregates the outputs at the end without preference to any model → Reduce the variance for algorithms with high variance.

# 1.2 Random Forest (RF)

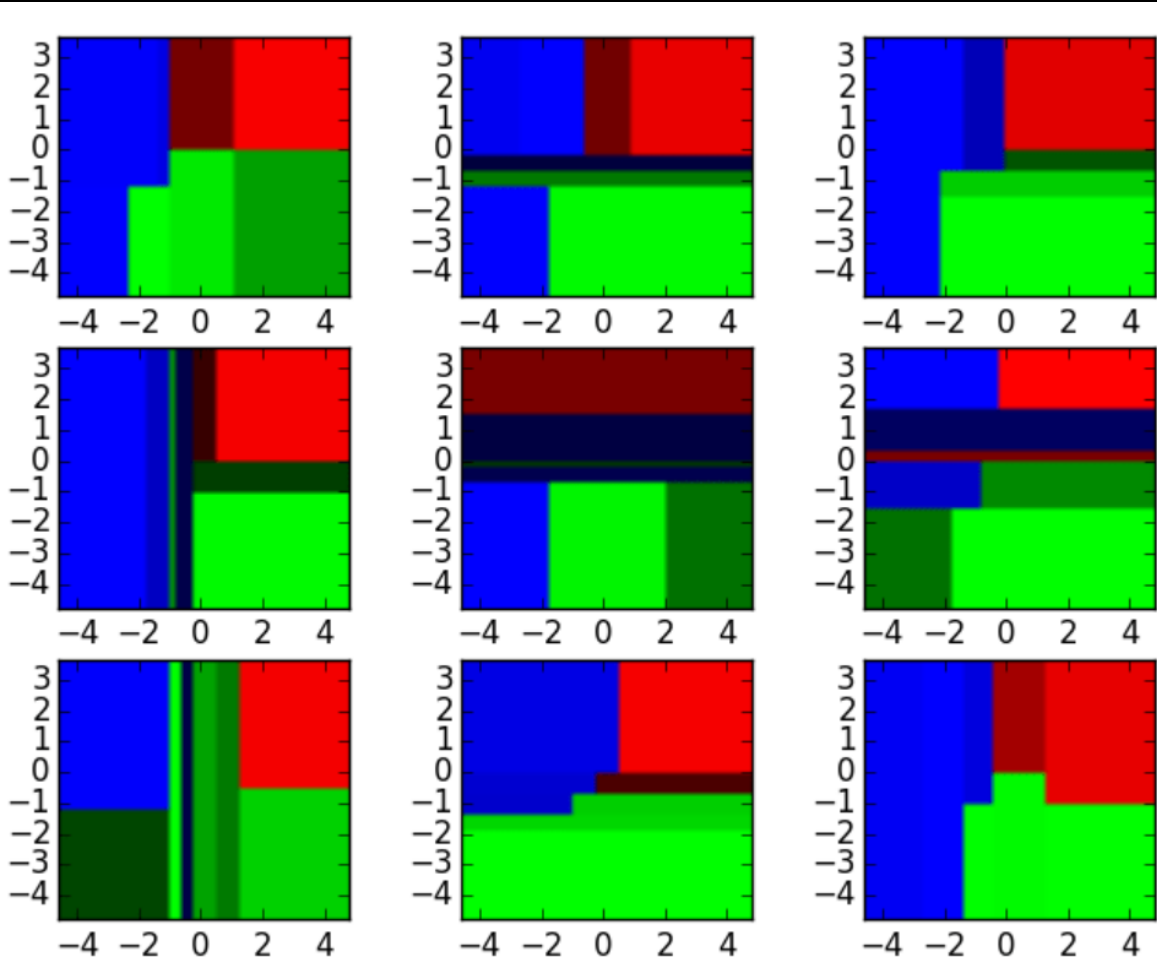
- Random Forest (RF) = bagging technique.
- RF constructs a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.
- RF >> Decision Tree (DT) (generally) because...
- DT = computationally expensive +
- sensitive to training data



# 1.2. RF = meta-estimator...

...which **aggregates many decision trees**, whereby:

- the number of features that can be split on at each node is limited to some percentage of the total (i.e. **hyperparameter**). → the ensemble model **does not rely too heavily on any individual feature + fair use of all potentially predictive features**.
- each tree draws a random sample from the original data set when generating its splits → adding a further element of randomness → prevents **overfitting**.

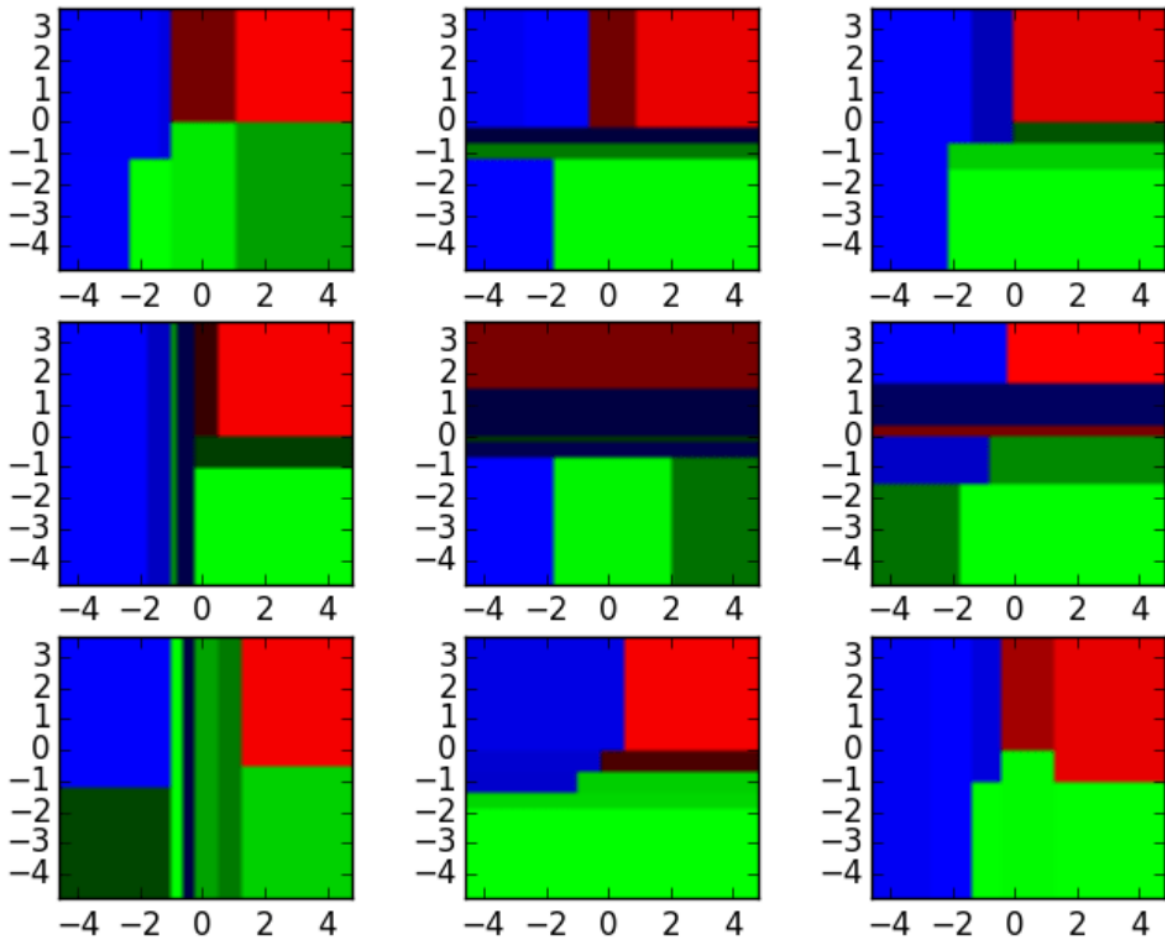


Nine Different Decision Tree Classifiers

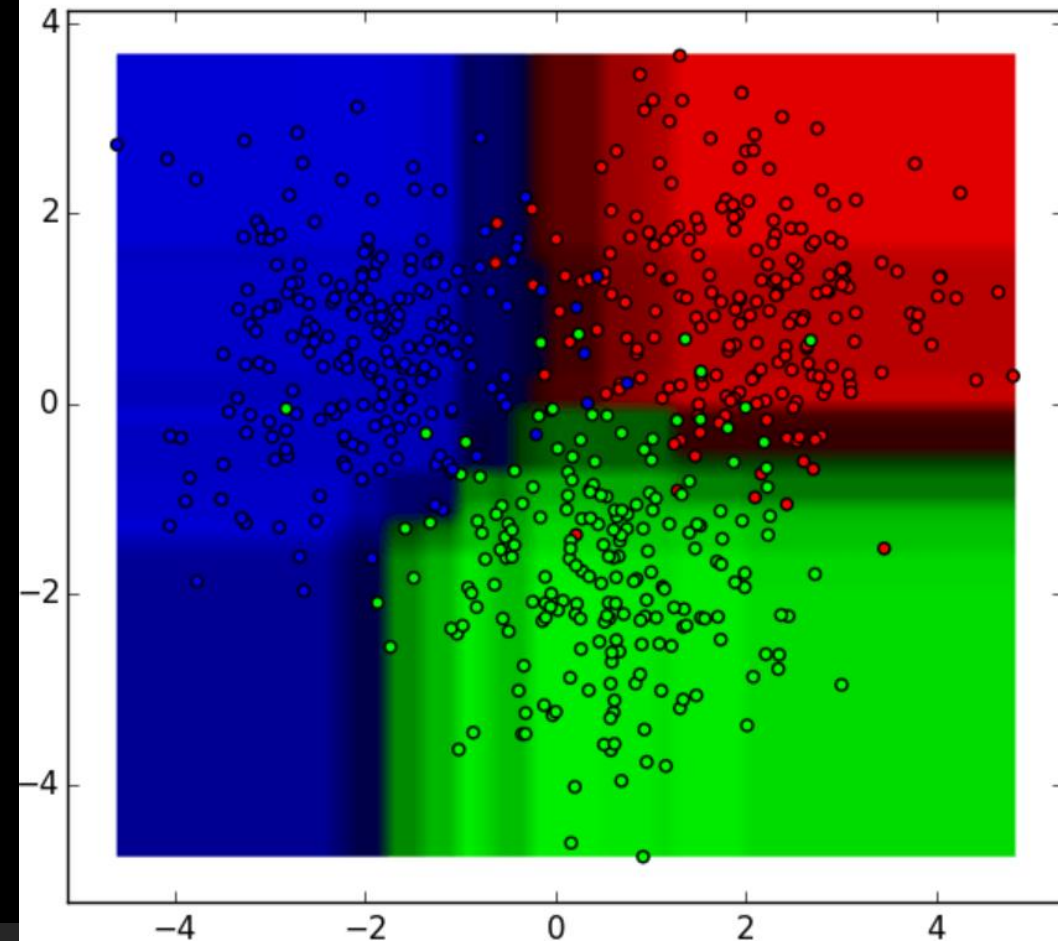


# Read more on RF @

<https://medium.com/swlh/random-forest-and-its-implementation-71824ced454f>



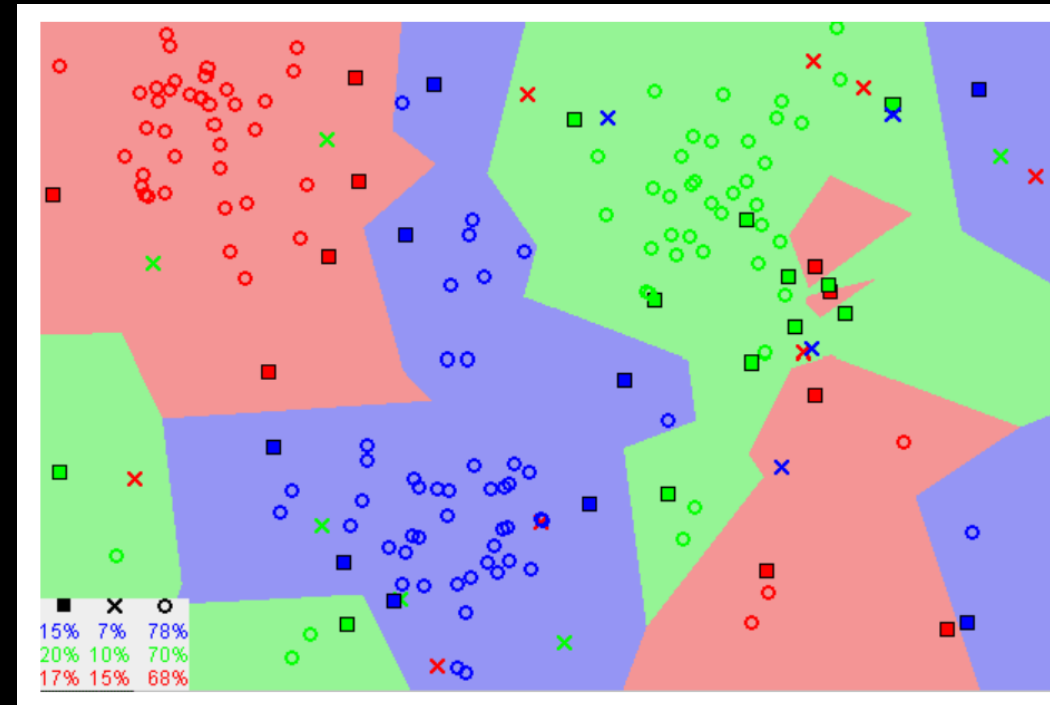
Nine Different Decision Tree Classifiers



Random Forest ensemble for the above Decision Tree classifiers

# 1.2 K-nearest neighbors (KNN)

Key assumption: similar things exist in close proximity



# 1.2 K-nearest neighbors (KNN)

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How to choosing the right value for K?

- Run KNN algorithm several times with different values of K
- Choose the K that reduces the number of errors we encounter while maintaining the algorithm's ability to predict accurately when it's given new data.

↓ K to 1 = predictions ↓ stable.

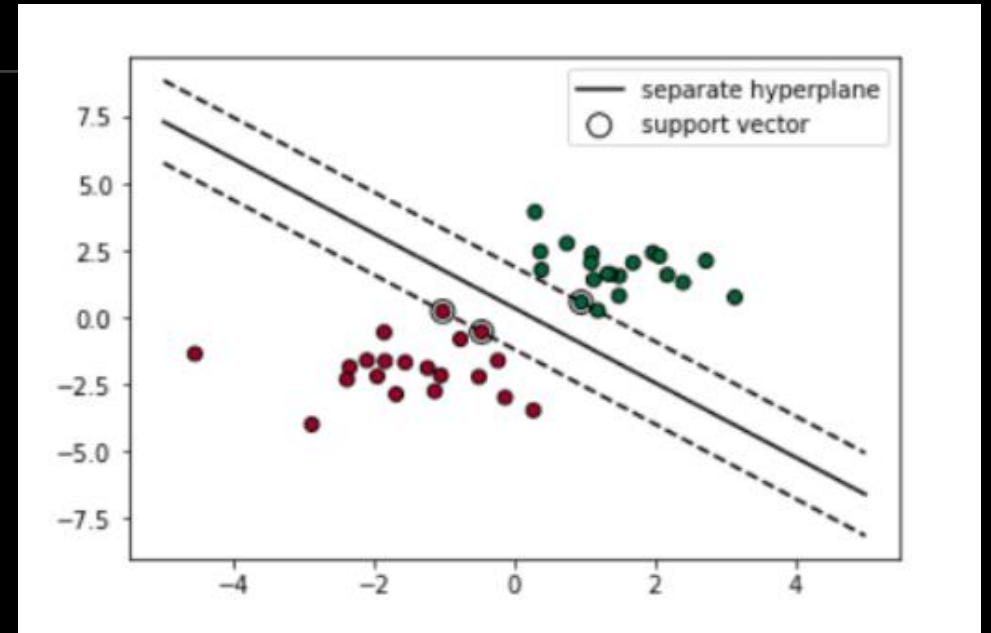
↑ K = predictions ↑ stable (due to majority voting / averaging), BUT @ the cost of increasing number of errors!

NOTE: If you take a majority vote (e.g. picking the mode in a classification problem) among labels, make K an odd number to have a tiebreaker.

# 1.2 Support Vector Machine (SVM)

Key idea: find the decision boundary to separate different classes and maximize the margin.

Simplest case = linear separable, 2-D



For more details on nonseparable cases & SVM, check

<https://towardsdatascience.com/support-vector-machine-simply-explained-fee28eba5496>

## 2. Model Evaluation Methods

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For your own self-reading, we will see some in practice 😊

<https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234>

# Further home readings?

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W7: Check Microsoft Azure ML Algorithm Cheat Sheet & blog posts on how to select the best ML algorithms.

W8: Required articles on word embeddings, word2vec and cosine similarity (also in W7 reading list)

# Practice time 😊

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Open your Google Colab/ Jupyter Notebook

# Practice time 😊

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<https://github.com/httn21uhh/Text-Analysis-for-Social-Sciences-in-Python>

→ W7\_supervisedmethods.ipynb + housing\_cali.csv

- Download them
- Run the files on your own laptop
- The iPython file is NOT meant for passive scrolling!



# This week...

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- See some supervised ML methods in action & evaluate the models
- Follow closely the illustrated examples and replicate yourself as the session proceeds.
- Raise your hands to ask questions at any point, including when you think things go too fast/slow for you.