Sequencing Legal DNA

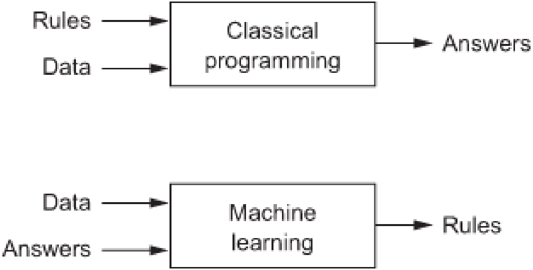
NLP for Law and Political Economy

4. Supervised Learning with Text

Weekly Q&A Page

bit.ly/NLP-QA04

What is machine learning?



- In classical computer programming, humans input the rules and the data, and the computer provides answers.
- In machine learning, humans input the data and the answers, and the computer learns the rules.

Machine Learning with Text Data

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- Some documents are unlabeled $\rightarrow$ we would like to train a model to machine-classify them.

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   - Interpret predictions using model explanation methods.
4. Empirical analysis
   - Produce statistics or predictions with the trained model.
   - **Answer the question / solve the problem.**

ML Essentials

Overview

Regression / Regularization

Binary Classification

Multi-Class Models

Osnabruegge, Ash, and Morelli 2020

Ensemble Learning with XGBoost

Three Types of (Standard) Machine Learning Problems

Determined by the data type of the outcome variable (or label):

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- **Binary classification**: two choices, normalized to zero and one.
  - e.g., guilty or innocent
- **Regression**: a one-dimensional, continuous, real-valued outcome.
  - e.g., number of days of prison assigned
- **Multinomial Classification**: Three or more discrete, un-ordered outcomes.
  - e.g., predict what judge is assigned to a case: Alito, Breyer, or Cardozo

What do ML Algorithms do? Minimize a cost function

- A typical cost function (or loss function) for regression problems is Mean Squared Error (MSE):

$$\mathrm{MSE}(\theta) = \frac{1}{n_D} \sum_{i=1}^{n_D} (h(x_i;\theta) - y_i)^2$$

  - n_D, the number of rows/observations
  - x, the matrix of predictors, with row x_i
  - y, the vector of outcomes, with item y_i
  - $h(x_i;\theta) = \hat{y}$ the model prediction (hypothesis)

Loss functions, more generally

- The loss function $L(\hat{\boldsymbol{y}}, \boldsymbol{y})$ assigns a score based on prediction and truth:
  - Should be bounded from below, with the minimum attained only for cases where the prediction is correct.
- The average loss for the test set is

$$\mathcal{L}(\theta) = \frac{1}{n_D} \sum_{i=1}^{n_D} L(h(\boldsymbol{x}_i; \theta), \boldsymbol{y}_i)$$

- The estimated parameter matrix θ solves

$$\hat{\theta} = \arg\min_{\theta} \mathcal{L}(\theta)$$

$\hookrightarrow$ optimizes over parameter space; treats the data as constants.

OLS Regression is Machine Learning

- Ordinary Least Squares Regression (OLS) assumes the functional form $f(x;\theta) = x_i'\theta$ and minimizes the mean squared error (MSE)

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- This minimand has a closed form solution

$$\hat{\theta} = (\boldsymbol{x}'\boldsymbol{x})^{-1}\boldsymbol{x}'\boldsymbol{y}$$

  - most machine learning models do **not** have a closed form solution $\rightarrow$ use numerical optimization (gradient descent).

$$\mathrm{MSE}(\theta) = \frac{1}{n_D}\sum_{i=1}^{n_D}(h(\theta;\boldsymbol{x}_i) - y_i)^2$$

- The partial derivative for feature j is

$$\frac{\partial \mathrm{MSE}}{\partial \theta_j} = \frac{2}{n_D}\sum_{i=1}^{n_D}(\underbrace{h(\theta;\boldsymbol{x}_i) - y_i}_{\text{error for this obs}}) \quad \underbrace{\frac{\partial h(\theta;\boldsymbol{x}_i)}{\partial \theta_j}}_{\text{how } \theta_j \text{ shifts } h(\cdot)}$$

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- The ***gradient*** ∇ gives the vector of these partial derivatives for all features:

$$\nabla_\theta \text{MSE} = \begin{bmatrix} \frac{\partial \text{MSE}}{\partial \theta_1} \\ \frac{\partial \text{MSE}}{\partial \theta_2} \\ \vdots \\ \frac{\partial \text{MSE}}{\partial \theta_j} \end{bmatrix}$$

- ***Gradient descent*** nudges θ against the gradient (the direction that reduces MSE):

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \text{MSE}$$

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- ***Stochastic* gradient descent (SGD)** computes the gradient for a single randomly sampled instance (at each iteration). Much faster, still works well.

Data Prep for Machine Learning

- Data Pre-Processing: See Geron Chapter 2 for pandas and sklearn syntax:
  - imputing missing values.
  - feature scaling (often helpful/necessary for ML models to work well)
    - if predictors are sparse (e.g. bag-of-words), use `StandardScaler(with_mean=False)`.
  - encoding categorical variables.
  - **Best practice: reproducible data pipeline**.

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- Train/Test Split:
  - ML models can achieve arbitrarily high accuracy in-sample, so performance should be evaluated out-of-sample.
  - standard approach: randomly sample 80% training dataset to learn parameters, form predictions in 20% testing dataset for evaluating performance.

Use Cross-Validation During Model Training

- Within the training set:
  - Use cross-validation with grid search to get model performance metrics across subsets of data using different hyperparameter specs.
  - Find the best hyperparameters for out-of-fold prediction in the training set.
- Then evaluate model performance in the test set using these hyperparameters.

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- Then evaluate model performance in the test set using these hyperparameters.
- Cross-validation is less common in deep learning, where training multiple models is too computationally expensive.
  - instead, use dropout and early stopping (next week).

Model Evaluation in Test Set

Evaluating a "good" model is context-dependent. Here are some basics.

Regression:

- mean squared error (MSE)
- R-squared (same ranking as MSE, but units are more interpretable)
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Classification:

- more complicated, but accuracy is a good baseline:
  accuracy = (# correct test-set predictions) / (# of test-set observations)
- What if one of the outcomes is over-represented – e.g., 19 out of 20? Then I can guess the modal class and get 95% accuracy.
  - Some alternative classifier metrics designed to address class imbalance (more below).

Regression models $\leftrightarrow$ Continuous outcome

- If the outcome is continuous (e.g., Y = tax revenues collected, or criminal sentence imposed in months of prison):
  - Need a regression model.
- Problems with OLS:
  - tends to over-fit training data.
  - cannot handle multicollinearity.

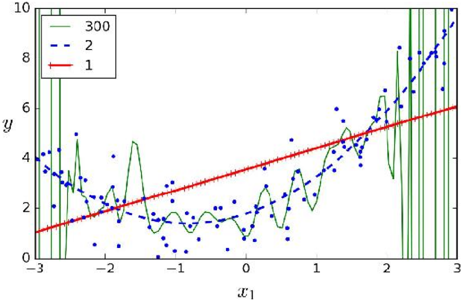

Figure 4-14. High-degree Polynomial Regression

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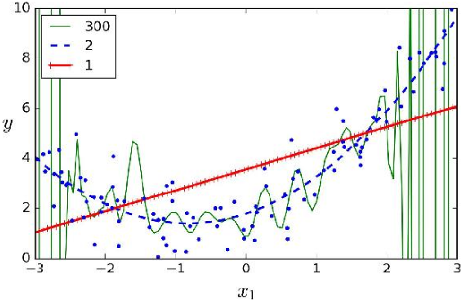

Figure 4-14. High-degree Polynomial Regression

- ***Regularization***: model training methods designed to reduce/prevent over-fitting.

Regularized Loss Function

$$\hat{\boldsymbol{\theta}} = \arg\min_{\theta} \frac{1}{n_D} \sum_{i=1}^{n_D} L(h(\boldsymbol{x}_i; \theta), \boldsymbol{y}_i) + \lambda R(\theta)$$

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- Elastic Net: $R_{enet} = \lambda_1 R_1 + \lambda_2 R_2$

Causal Graphs Activity

https://padlet.com/eash44/c0j5x4dwfc1evhgi

Binary Outcome $\leftrightarrow$ Binary Classification

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  - The standard approach is to apply a transformation (e.g. sigmoid/logit) to normalize $\hat{y} \in [0, 1]$.
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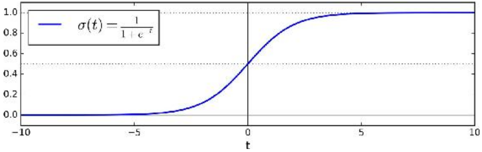
- The binary cross-entropy (or log loss) is:

$$L(\theta) = \underbrace{-\frac{1}{n_D}}_{\text{negative}} \sum_{i=1}^{n_D} [\underbrace{y_i}_{y_i=1} \underbrace{\log(\hat{y}_i)}_{\text{log prob} y_i=1} + \underbrace{(1-y_i)}_{y_i=0} \underbrace{\log(1-\hat{y}_i)}_{\text{log prob} y_i=0}]$$

- In **logistic regression** we use a sigmoid transformation:

$$\hat{y} = \text{sigmoid}(\boldsymbol{x} \cdot \theta) = \frac{1}{1 + \exp(-\boldsymbol{x} \cdot \theta)}$$



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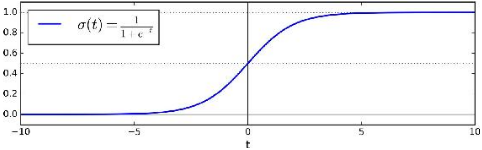

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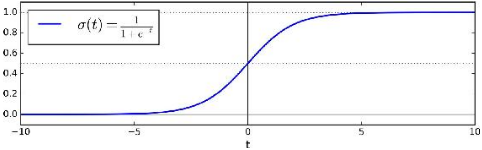

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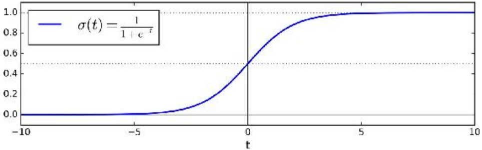

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- Like linear regression, logistic regression can be regularized with L1 or L2 penalties.

A **Confusion Matrix** is a nice way to visualize classifier performance:

		Predicted Class	
		Negative	Positive
True Class	Negative	**# True Negatives**	# False Positives
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$$\text{Recall (for positive class)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- Recall decreases with false negatives. "When this outcome occurs, I don't miss it."

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F_1 **score** = the harmonic mean of precision and recall:

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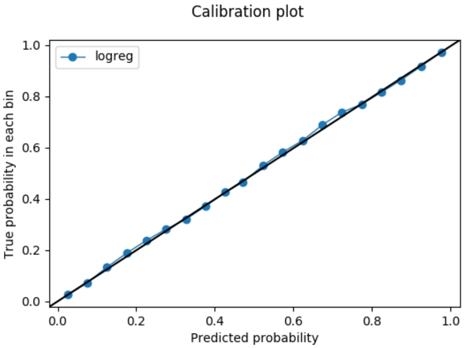
AUC-ROC = Area Under the Receiver Operating Characteristic Curve

- provides an aggregate measure of performance across all possible classification thresholds.
- Interpretation: randomly sample one positive and one negative example. AUC = probability that the model correctly guesses which is which.

Evaluating Classification Models: Calibration Curves



- Plotting the binned fraction in a category (Y axis) against the predicted probability in a category (X axis):
- Provides evidence of whether the classifer is replicating the conditional distribution of the outcome.

```
from seaborn import regplot
regplot(y_test, y_pred, x_bins=20)
```

Application: Predicting Political Party from Text

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  - Label Y = party of speaker (Conservative or Labour)

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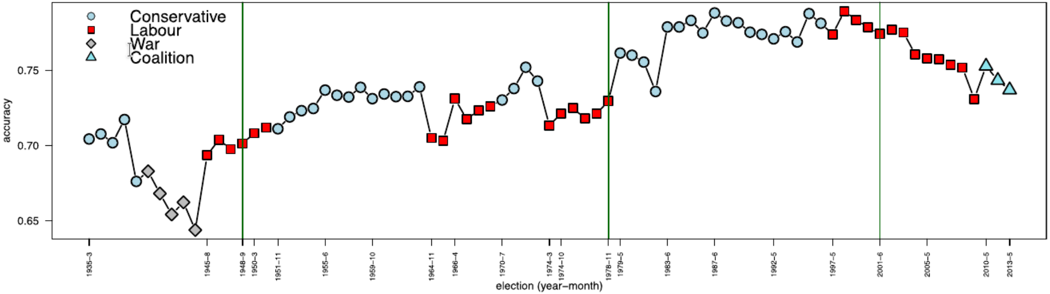
- Machine Learning Problem:
  - Corpus D = 3.5M U.K. parliament speeches, 1935-2013.
  - Label Y = party of speaker (Conservative or Labour)

In years that classifier is more accurate, speech is more polarized:



Multiple Classes: Setup

- The outcome is $y_i \in \{1, ..., k, ..., n_y\}$ output classes, which can also be represented as a one-hot vector
$$\boldsymbol{y}_i = \{\mathbf{1}[y_i = 1], ..., \mathbf{1}[y_i = n_y]\}$$

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- We want to learn a vector function

$$\boldsymbol{y} = \boldsymbol{h}(\boldsymbol{x}, \theta)$$

taking text features $\boldsymbol{x}$ as inputs and outputting a vector of probabilities across outcome classes:

$$\hat{\boldsymbol{y}} = \{\hat{y}^1, ..., \hat{y}^{n_y}\}, \sum_{k=1}^{n_y} \hat{y}^k = 1, \hat{y}^k \geq 0 \ \forall k$$

- for prediction step, can select the highest-probability class:

$$\tilde{y} = \arg\max_k \hat{y}_{[k]}$$

Categorical Cross Entropy

- The standard loss function in multinomial classification is **categorical cross entropy**:

$$L(\theta) = -\sum_{k=1}^{n_y} \boldsymbol{y}^k \log(\hat{y}^k(\boldsymbol{x}, \theta))$$

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- Since there is just one true class ($y = 1$ for one class k^*, and zero for others), simplifies to
$$L(\theta) = -\log(\hat{y}^{k^*}(\boldsymbol{x}, \theta))$$
  - Rewards putting higher probability on the true class, ignores distribution of probabilities on other classes.
  - function is convex $\rightarrow$ gradient descent will find the optimum.

Multinomial Logistic Regression

Multinomial logistic regression computes probabilities for each class k using the softmax transformation

$$\hat{y}_k(\boldsymbol{x}_i) = \Pr(y_i = k) = \frac{\exp(\theta_k' \boldsymbol{x}_i)}{\sum_{l=1}^{n_y} \exp(\theta_l' \boldsymbol{x}_i)}$$

- softmax is the multiclass generalization of sigmoid $\rightarrow$ can then interpret $\hat{y}$ as probabilities.
- n_x features and n_y output classes $\rightarrow$ there is a $n_y \times n_x$ parameter matrix Θ, where the parameters for each class θ_k are stored as rows.

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The **L2-penalized logistic regression** has loss function

$$\mathcal{L}(\theta) = -\frac{1}{n_D} \sum_{i=1}^{n_D} \log \frac{\exp(\theta'_{k^*} \boldsymbol{x}_i)}{\sum_{l=1}^{n_y} \exp(\theta'_l \boldsymbol{x}_i)} + \lambda \sum_{j=1}^{n_x} \sum_{k=1}^{n_y} (\theta_{[j,k]})^2$$

- λ = strength of L2 penalty (could also add lasso penalty)
  - as before, predictors should be scaled to the same variance.

		Predicted Class		
		Class A	Class B	Class C
True Class	Class A	Correct A	A, classed as B	A, classed as C
	Class B	B, classed as A	Correct B	B, classed as C
	Class C	C, classed as A	C, classed as B	Correct C

More generally, with **multi-class confusion matrix** M with items M_{ij} (row i, column j):

$$\text{Precision for } k = \frac{\text{True Positives for } k}{\text{True Positives for k} + \text{False Positives for } k} = \frac{M_{kk}}{\sum_l M_{lk}}$$

$$\text{Recall for } k = \frac{\text{True Positives for } k}{\text{True Positives for } k + \text{False Negatives for } k} = \frac{M_{kk}}{\sum_l M_{kl}}$$

$$F_1(k) = 2 \times \frac{\text{precision}(k) \times \text{recall}(k)}{\text{precision}(k) + \text{recall}(k)}$$

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Can average these metrics across classes to get aggregate metrics.

- e.g., balanced accuracy = unweighted average of recalls across classes.
- can weight classes by their frequency in dataset

Cross-Domain (Transfer) Learning

- A recent but now widespread approach to machine learning is **transfer learning**:
  - train a model in a big labeled dataset
  - apply in a smaller (mostly) unlabeled dataset

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- A recent but now widespread approach to machine learning is **transfer learning**:
  - train a model in a big labeled dataset
  - apply in a smaller (mostly) unlabeled dataset
- In NLP:
  - transfer learning is intuitive because NLP tasks share common knowledge about language.
  - labeled data is scarce/expensive, so learn tasks on tons of unlabeled data.
  - reflected in success of pre-trained models, e.g. BERT and GPT.

Osnabruegge, Ash, and Morelli 2020

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- Learn to predict political topics from text in a labeled corpus (party manifestos from Comparative Manifesto Project)
- Apply model to classify topics in unlabeled corpus (parliamentary speeches).
- Use for empirical analysis of electoral institutions and speech content.

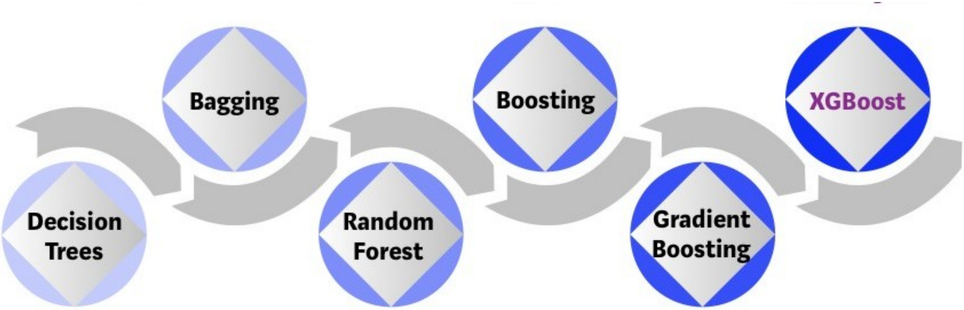
Overview of Text Analysis Methods

	Dictionaries (Custom)	Dictionaries (Generic)	Topic Modeling	Within-Domain Supervised Learning	Cross-Domain Supervised Learning
Design/Annotation Costs	High	Low	Low	High	Moderate
Specificity	High	Moderate	Low	High	Moderate
Interpretability	High	High	Moderate	High	High
Validatability	Low	Low	Low	High	High

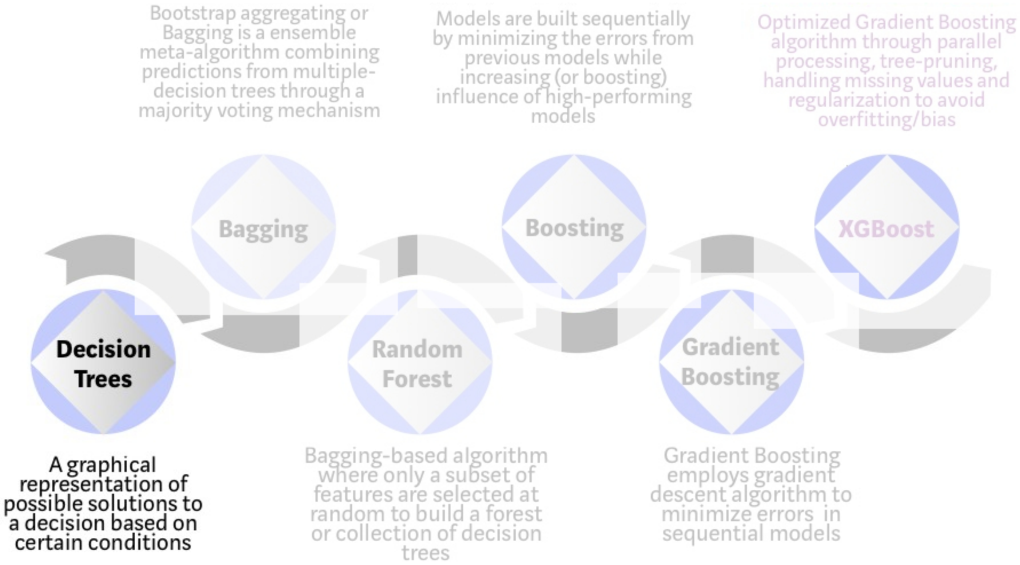
Breakout Groups: Section Responses

- See links in the chat.

XGBoost: Overview



XGBoost Ingredients: Decision Trees



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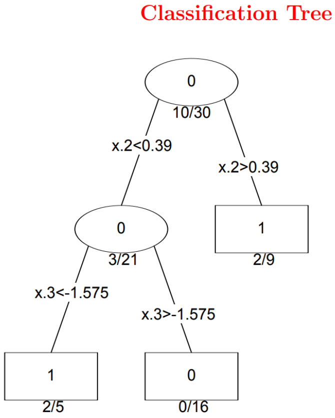
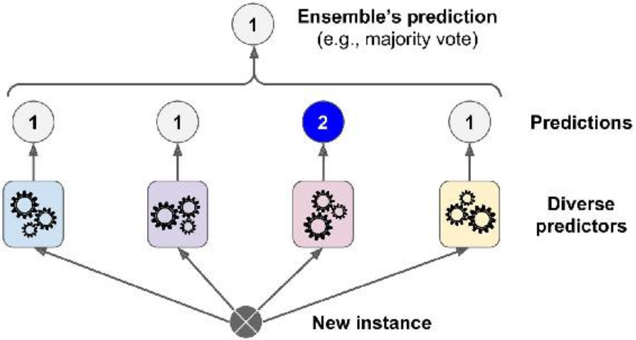


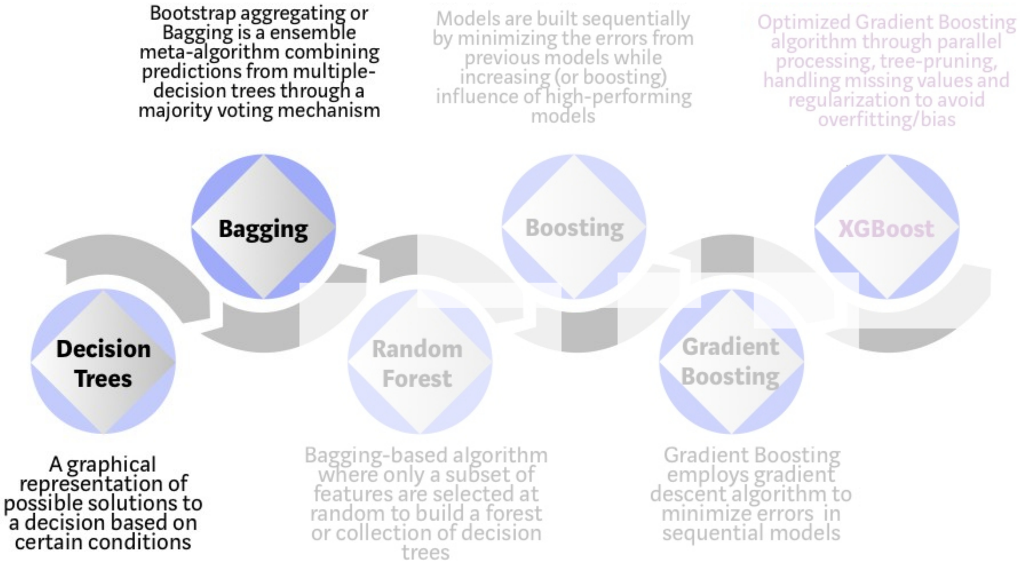
- Decision trees learn a series of binary splits in the data based on hard thresholds.
  - if yes, go right; if no, go left.
- Can have additional splits as you move through the tree.
- fast and interpretable, but performance is often poor.

Voting Classifiers



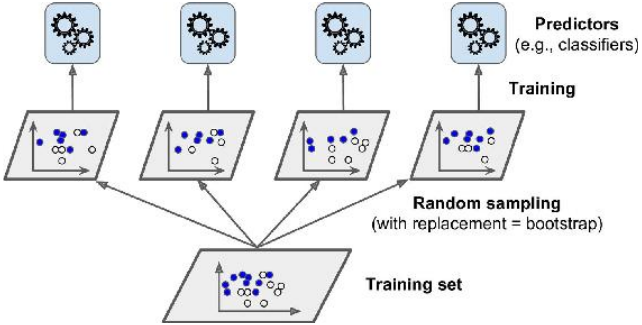
- voting classifiers (ensembles of different models that vote on the prediction) generally out-perform the best classifier in the ensemble.
  - more diverse algorithms will make different types of errors, and improve your ensemble's robustness.

XGBoost Ingredients: Bootstrapping



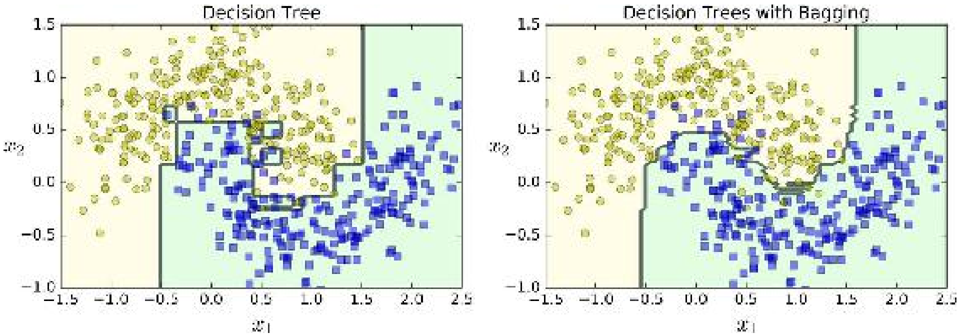
Bootstrapping

- Rather than use the same data on different classifiers, one can use different subsets of the data on the same classifier:



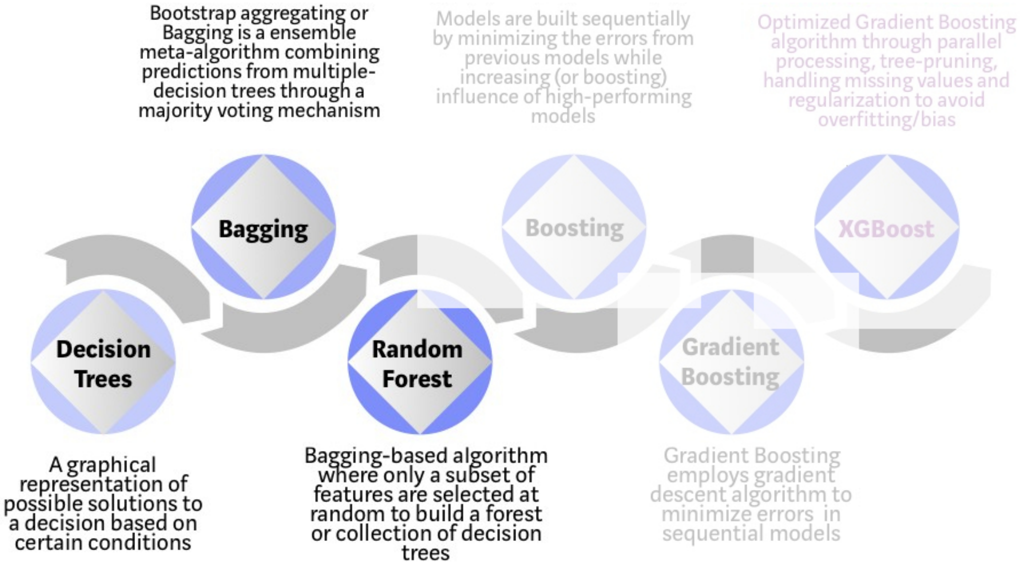
  - can also use different subsets of features across subclassifiers.

Bootstrapping Benefits



- A bootstraped ensemble generally has a similar bias but lower variance than a single predictor trained on all the data.
- Predictors can be trained in parallel using separate CPU cores.

XGBoost Ingredients: Random Forests



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Random Forests are optimized ensembles of bootstrapped decision trees:

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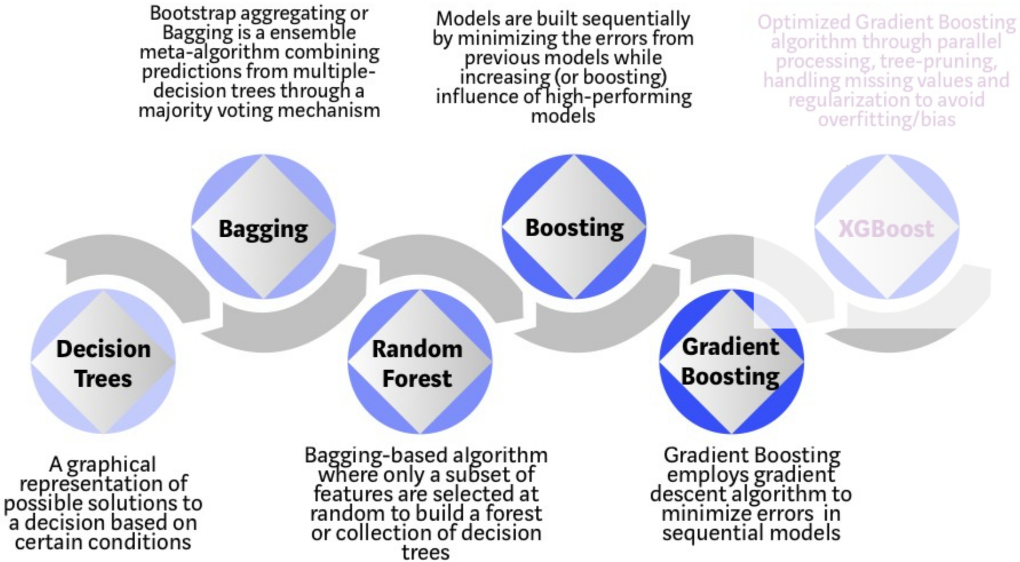
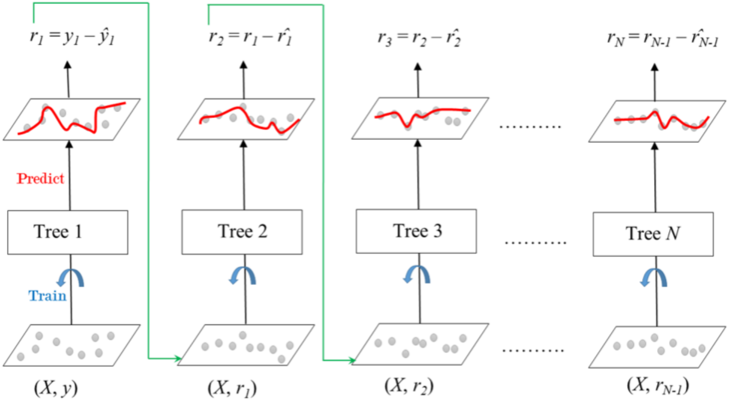
3. For each tree, error rate is computed using data outside its bootstrap sample.

XGBoost Ingredients: Gradient Boosting



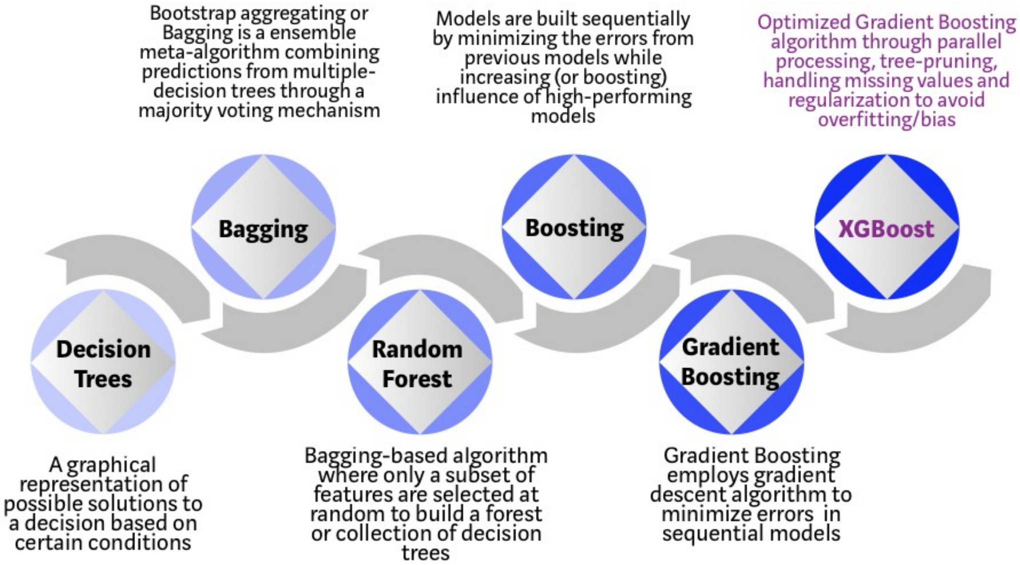
Gradient Boosting Machines

- Gradient boosting refers to an additive ensemble of trees:



- Adds additional layers of trees to fit the residuals of the first layers

XGBoost Ingredients



XGBoost

- Feurer et al (2018) find that XGBoost beats a sophisticated AutoML procedure with grid search over 15 classifiers and 18 data preprocessors.
- A good starting point for any machine learning task.

- easy to use
- actively developed
- efficient / parallelizable
- provides model explanations
- takes sparse matrices as input

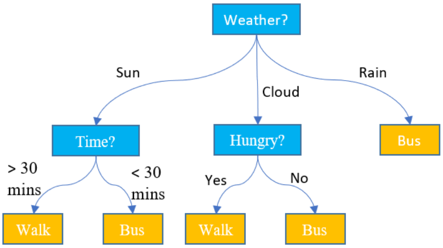
```
from xgboost import XGBClassifier
model = XGBClassifier()

model.fit(X_train, y_train,
          early_stopping_rounds=10,
          eval_metric="logloss",
          eval_set=[(X_eval, y_eval)]
          )

y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
```

Tree Ensembles are Black Boxes

- Small decision trees have the advantage of being highly interpretable.



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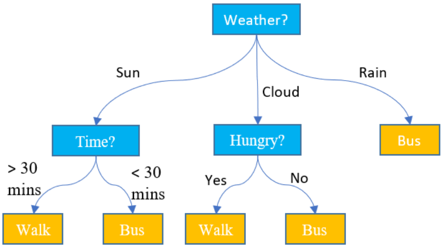
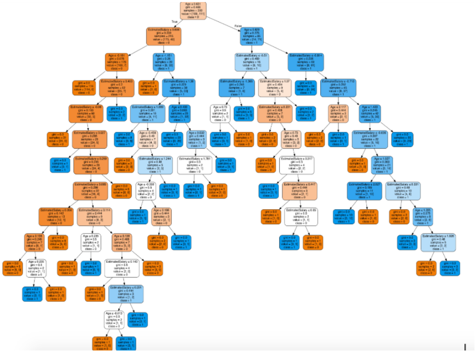




- Larger trees and ensembles (e.g. XGBoost) lose this nice feature.
- Best-performing ML models are hard to interpret because they use lots of features and exploit non-linearities and interactions.

Interpreting Tree Ensembles

XGBoost's Feature Importance Metric:

- At each decision node, compute **information gain** for feature j **(change in predicted probability**).
- Average across all nodes for each j.

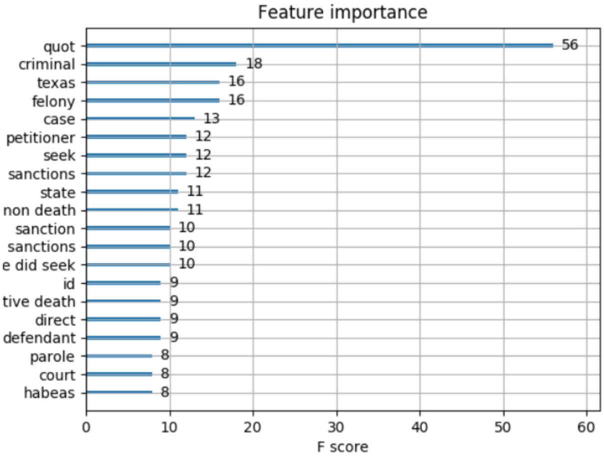
Ranks predictors by their relative contributions.

```
from xgboost import plot_importance
plot_importance(xgb_reg, max_num_features=10)
```

Feature Importance

```
from xgboost import plot_importance
plot_importance(xgb_reg, max_num_features=20)
```

```
<IPython.core.display.Javascript object>
```



- XGBoost provides a metric of feature importance that summarizes how well each feature contributes to predictive accuracy.

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6. Answer the research question!