Building a Robot Judge: Data Science for Decision-Making

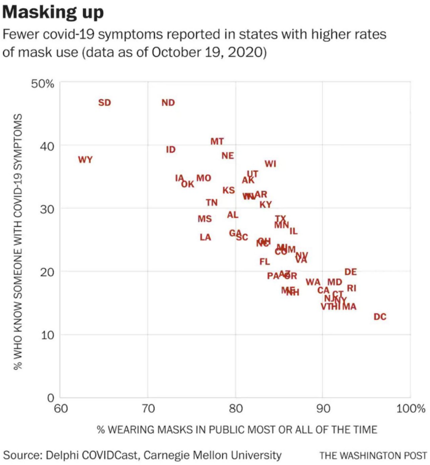
5. Classification

October 25, 2021

Q&A Page

https://padlet.com/eash44/90hgznjwl34fd97j

Week 2 Review: Four Types of Confounders



https://twitter.com/ASlavitt/status/1319870491063177216

Recall that there are four types of confounders. based on the first letter your last name, think of an example confounder for this proposed causal relationship.

1. [A-G] positively correlated with outcome, positively correlated with treatment
   1.1 [H-M] positively correlated with outcome, negatively correlated with treatment
   1.2 [N-S] negatively correlated with outcome, positively correlated with treatment
   1.3 [T-Z] negatively correlated with outcome, negatively correlated with treatment

Write it down privately. In 3 minutes, we will type it into the zoom chat. Put your group #, the confounder, and which direction is the bias of the estimate (up or down), relative to the true causal effect (if this is the only confounder).

Week 3 Review: What line # has a bug?

Private zoom chat to Claudia your answer (90 seconds)

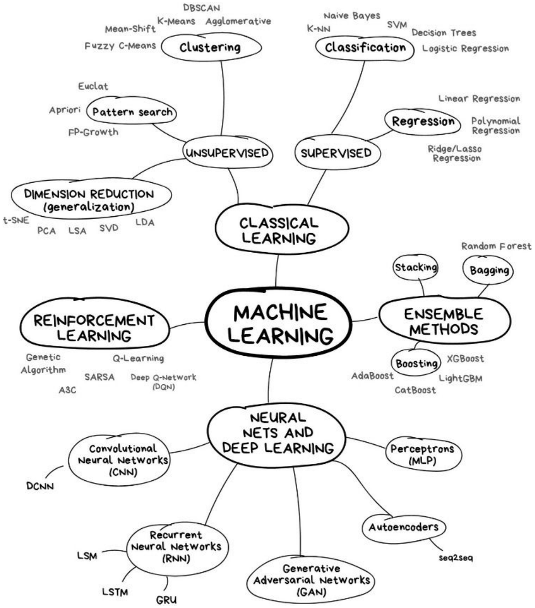
```
1 X_train, X_test, y_train, y_test = train_test_split(X,y_true)
2 lasso = Lasso()
3 lasso.fit(X_train, y_train)
4 y_pred = lasso.predict(X)
5 mae = mean_absolute_error(y_true,y_pred)
```

- Note: mean absolute error $(\sum|y-\hat{y}|)$ is an alternative regression metric that is less sensitive to outliers than mean squared error $(\sum(y-\hat{y})^2)$.

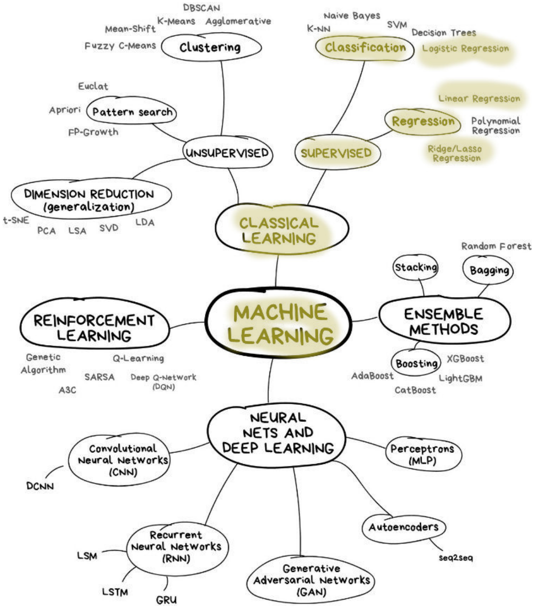
Week 4 Review: Confounding factors for a tax cut (3 minutes)

- Imagine that cantons Zurich and Zug each enact a tax cut and you estimate a negative effect on local employment using **two-way fixed-effects regression**. What are some potential confounding factors that would bias this estimate?
  - write them down privately, we will type them in the chat in 3 minutes

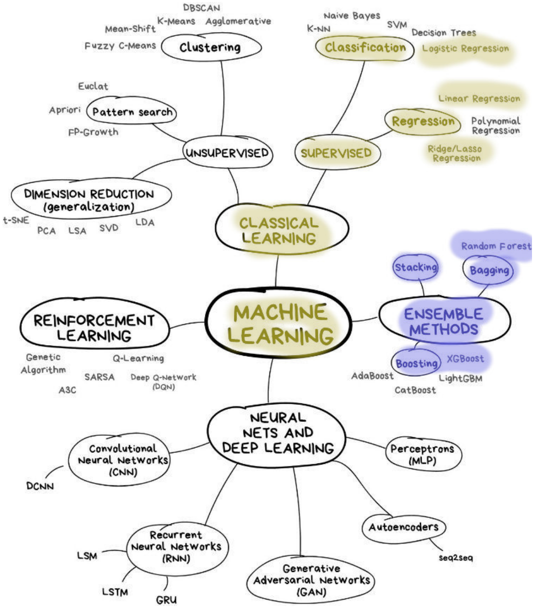
The Machine Learning Landscape



What we have done so far



What we will do today



Outline

Binary Classifier Metrics

Multi-Class Models

Ensemble Learning with XGBoost

Response Essays

Machine learning metrics

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  - accuracy = (# correct test-set predictions) / (# of test-set observations)

Machine learning metrics

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- For classification, things are more complicated.
- As a (good) baseline, we have:
  - accuracy = (# correct test-set predictions) / (# of test-set observations)
- But what if one of the outcomes is rare – e.g., one out of 20?
  - Then I can guess the modal class and get 95% accuracy.
- As we will see, there are a range of other useful metrics besides accuracy for evaluating classifier performance.

Confusion Matrix

A nice way to visualize classifier performance:

		Predicted Class	
		Negative	Positive
True Class	Negative	**# True Negatives**	# False Positives
	Positive	# False Negatives	**# True Positives**

- Cell values give counts in the test set.

```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred)
```

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{False Negatives} + \text{True Negatives}}$$

Precision and Recall

		Predicted Class	
		Negative	Positive
True Class	Negative	# True Negatives	**# False Positives**
	Positive	**# False Negatives**	**# True Positives**

```
from sklearn.metrics import precision_score, recall_score
precision_score(y_test,y_pred)
recall_score(y_test,y_pred)
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- Precision decreases with false positives. "When I guess this outcome, I tend to guess correctly."

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- Precision decreases with false positives. "When I guess this outcome, I tend to guess correctly."

$$\text{Recall (for positive class)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

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

Note: sckit-learn will produce precision/recall for $Y = 1$ by default

Trading off precision and recall

- Recall our decision framework:
  - a decision-maker who has to make a decision W, that will produce some value or benefit, conditional on the value of Y:
$$V = u(W, Y)$$
- One can imagine decision contexts where precision/recall should be valued asymmetrically. This is part of the function $u(W, Y)$.

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- One can imagine decision contexts where precision/recall should be valued asymmetrically. This is part of the function $u(W, Y)$.
- **For these decisions, would you prefer high precision or high recall?**
  1. deciding "send to prison" in court
  2. detecting bombs during flight screening
- send your answer via private zoom chat to Claudia – 60 seconds.

Balanced Accuracy and F1 Score

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- A standard metric in this case is **balanced accuracy** = the average recall in both classes:

$$\text{Balanced Accuracy} = \frac{1}{2}\left(\frac{\text{TP}}{\text{TP} + \text{FN}} + \frac{\text{TN}}{\text{TN} + \text{FP}}\right)$$

  - $\rightarrow$ equal to accuracy when classes are balanced, or performance is the same across classes.

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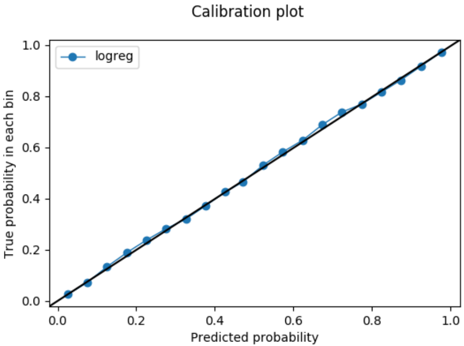
  - $\rightarrow$ equal to accuracy when classes are balanced, or performance is the same across classes.
- Another standard metric is F_1 score = the harmonic mean of precision and recall:

$$F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

  - penalizes both false positives and false negatives. still ignores true negatives.

```
from sklearn.metrics import balanced_accuracy_score, f1_score
balanced_accuracy_score(y_test,y_pred)
f1_score(y_test,y_pred) # gives values for both classes
```

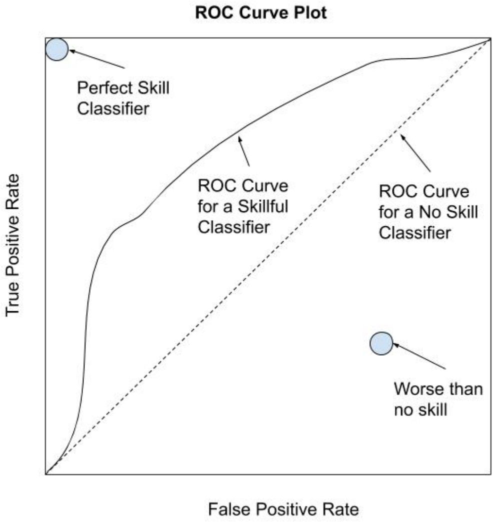
Evaluating Classification Models: Calibration Curves



- 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)
```

ROC Curve and AUC



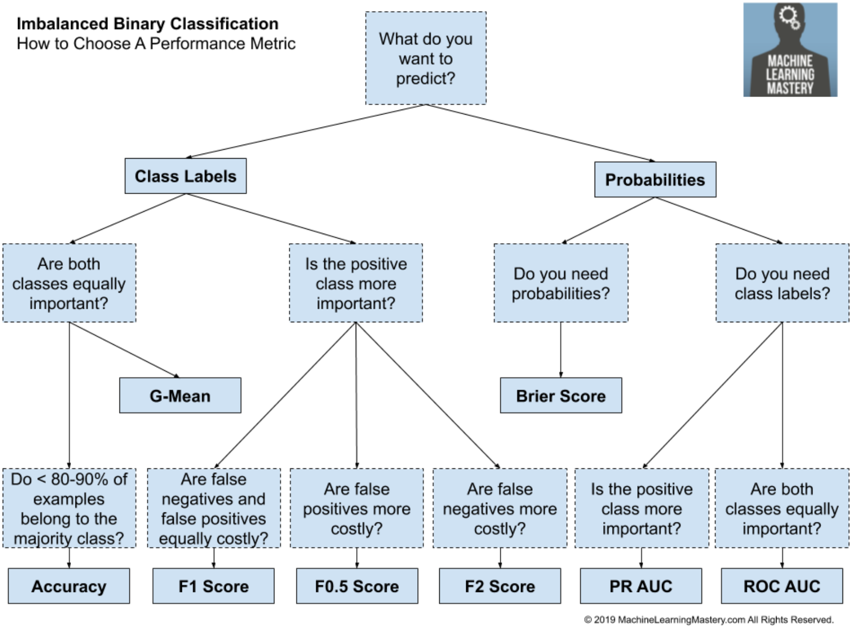
AUC = area under the (ROC) curve

- provides an aggregate measure of performance across all possible classification thresholds.

Interpreting AUC:

- = probability that the model (correctly) ranks a random positive example more highly than a random negative example.

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,y_pred)
```



See details in "Tour of evaluation metrics for imbalanced classification" (on syllabus).

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Multi-Class Models

Many interesting machine learning problems involve multiple un-ordered categories:

- categorizing a case by area of law.
- predicting the political party of a speaker in a multi-party system.
- predicting authorship from documents
- image classification / object detection

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

$$\boldsymbol{y}_i = \{\mathbf{1}[y_i = 1], ..., \mathbf{1}[y_i = n_y]\}$$

Multiple Classes: Setup

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$$\boldsymbol{y}_i = \{\mathbf{1}[y_i = 1], ..., \mathbf{1}[y_i = n_y]\}$$
- We want to learn a vector function
$$\boldsymbol{y} = \boldsymbol{h}(\boldsymbol{x}, \theta)$$
outputting a vector of probabilities across outcomes as a function of the inputs:
$$\hat{\boldsymbol{y}} = \{\hat{y}^1, ..., \hat{y}^{n_y}\}, \hat{y}^k \in [0, 1] \ \forall k$$
  - for prediction, 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**:

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

  - measures dissimilarity between the true label distribution $\boldsymbol{y}$ and the predicted label distribution $\hat{\boldsymbol{y}}$.

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  - measures dissimilarity between the true label distribution $\boldsymbol{y}$ and the predicted label distribution $\hat{\boldsymbol{y}}$.
- Since there is just one true class ($y = 1$ for one class k^*, and zero for others), simplifies to

$$L(\theta) = -\log(\hat{\boldsymbol{y}}_{[k^*]}(\boldsymbol{x}, \theta))$$

  - 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. 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.
- the prediction $y_i \in \{1, ..., n_y\}$ is determined by the highest-probability category.

Regularized Multinomial Logistic

- The L2-penalized logistic regression loss (the default in sklearn) is

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

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

```
from sklearn.linear_model import LogisticRegression
logit = LogisticRegression()
logit.fit(X,y)
```

  - if y is categorical, sklearn automatically uses multinomial logistic

Multi-Class Confusion Matrix

		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, can have a confusion matrix M with items M_{ij} (row i, column j).

Multi-Class Performance Metrics

Confusion matrix M with items M_{ij} (row i, column j).

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

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

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

- in sklearn, syntax is the same as binary case.

Metrics for whole model

$$\text{Balanced Accuracy} = \frac{1}{n_y} \sum_{k} \text{Recall for } k$$

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- **Macro-averaging**: average of the per-class precision, recall, and F1, e.g.

$$F_1 = \frac{1}{n_y} \sum_{k=1}^{n_y} F_1(k)$$

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  - weights all classes equally
- Both of these approaches up-weight frequent classes:
  - **Micro-averaging**: Compute model-level sums for true positives, false positives, and false negatives; compute precision/recall from model sums.
  - "**Weighted**": computed like macro-averaging, but classes are weighted by true frequency.

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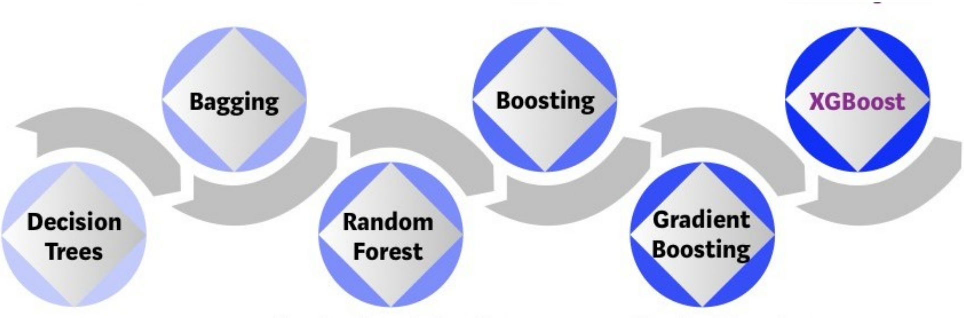
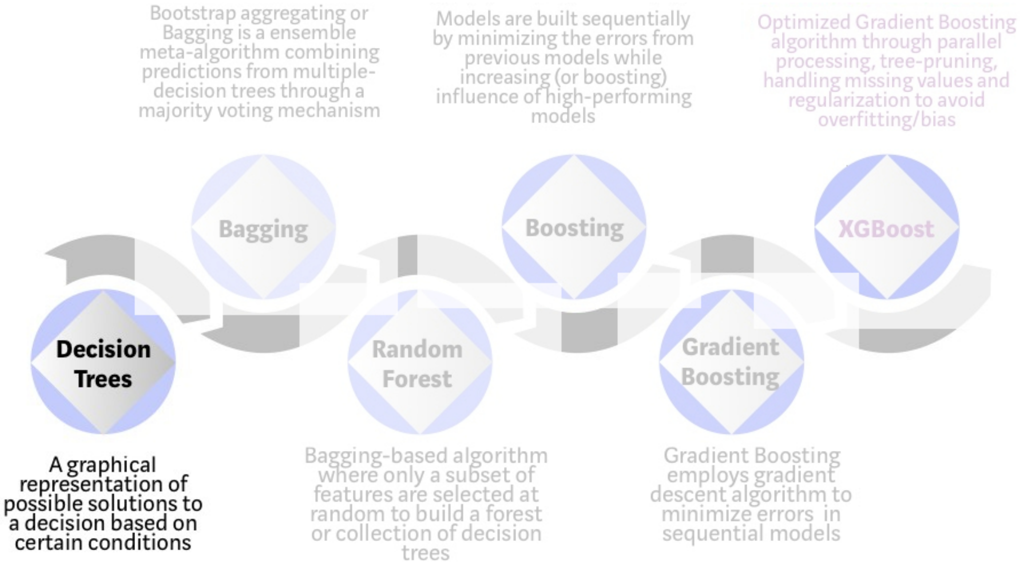
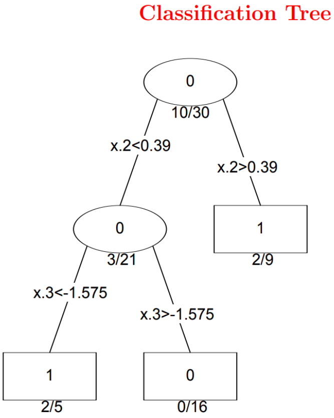
XGBoost: Overview



XGBoost Ingredients: Decision Trees

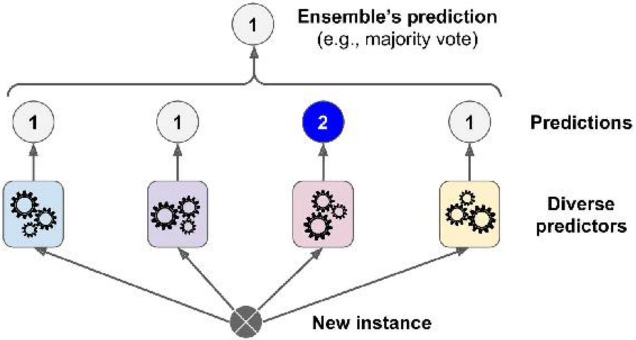


Decision Trees



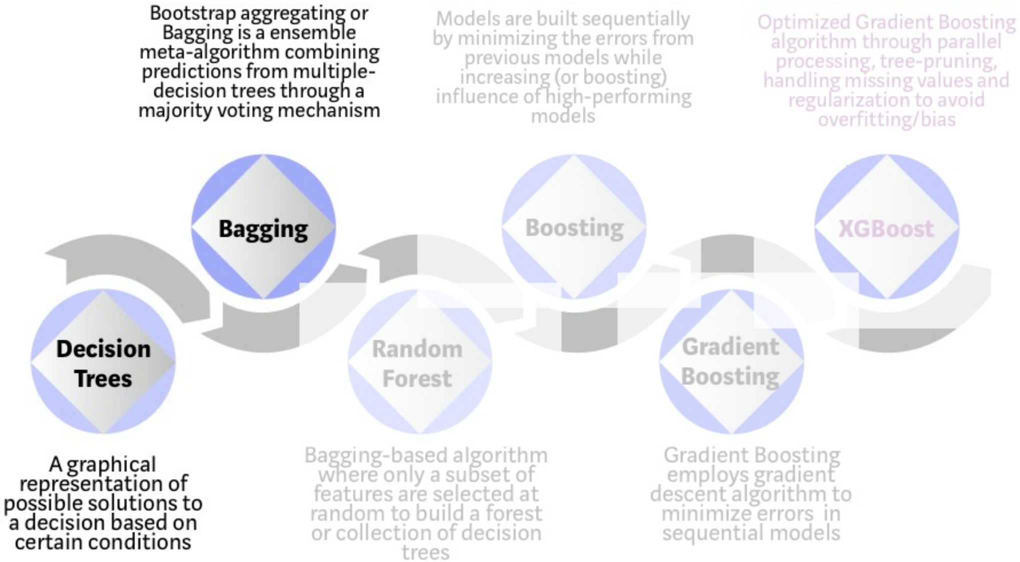
- Decision trees learn a series of binary splits in the data based on hard thresholds.
  - if yes, go right; if no, go left.
- Can have additional splits as you move through the tree.
- fast and interpretable, but performance is often poor.

Voting Classifiers



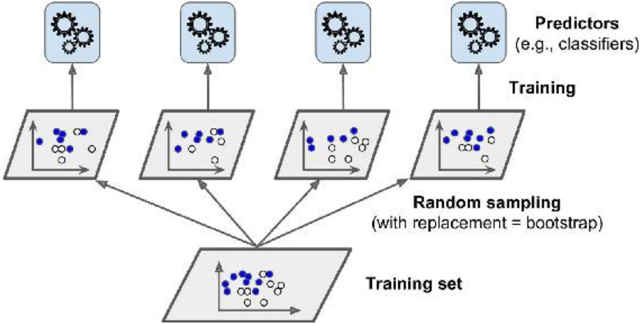
- voting classifiers (ensembles of different models that vote on the prediction) generally out-perform the best classifier in the ensemble.
  - more diverse algorithms will make different types of errors, and improve your ensemble's robustness.

XGBoost Ingredients: Bootstrapping



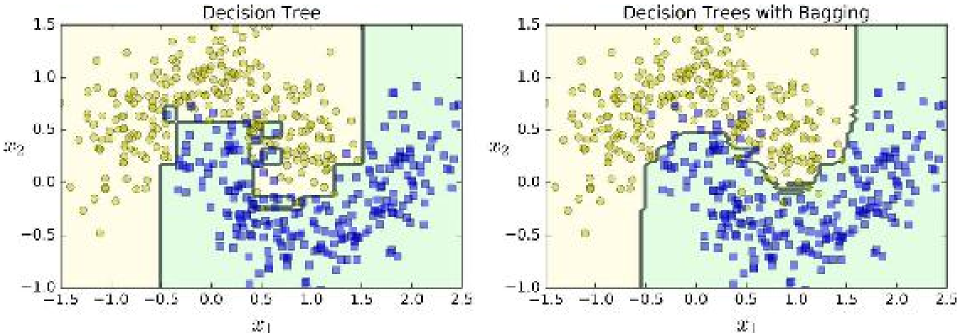
Bootstrapping

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



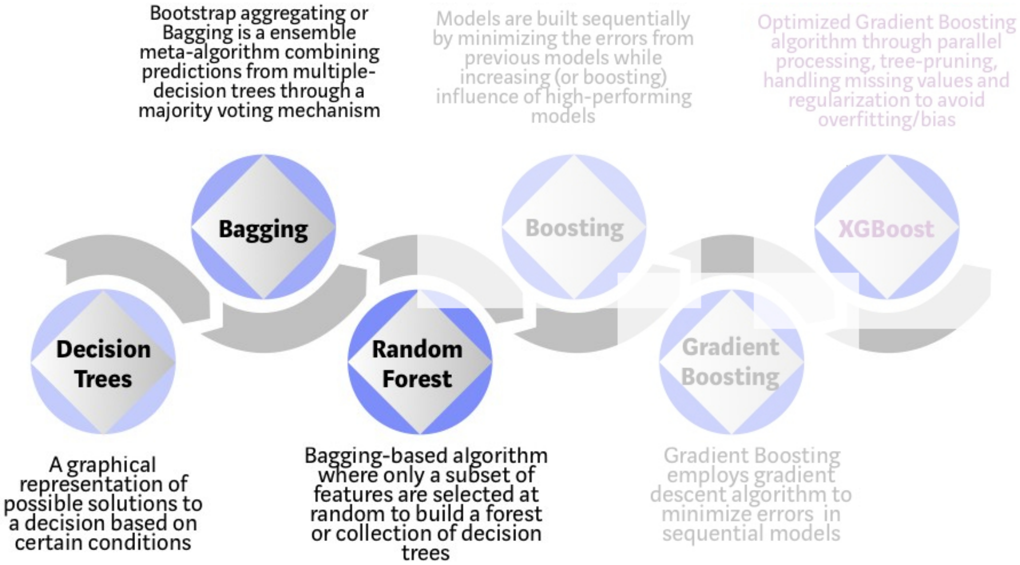
  - can also use different subsets of features across subclassifiers.

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



Random Forests

Random Forests are optimized ensembles of bootstrapped decision trees:

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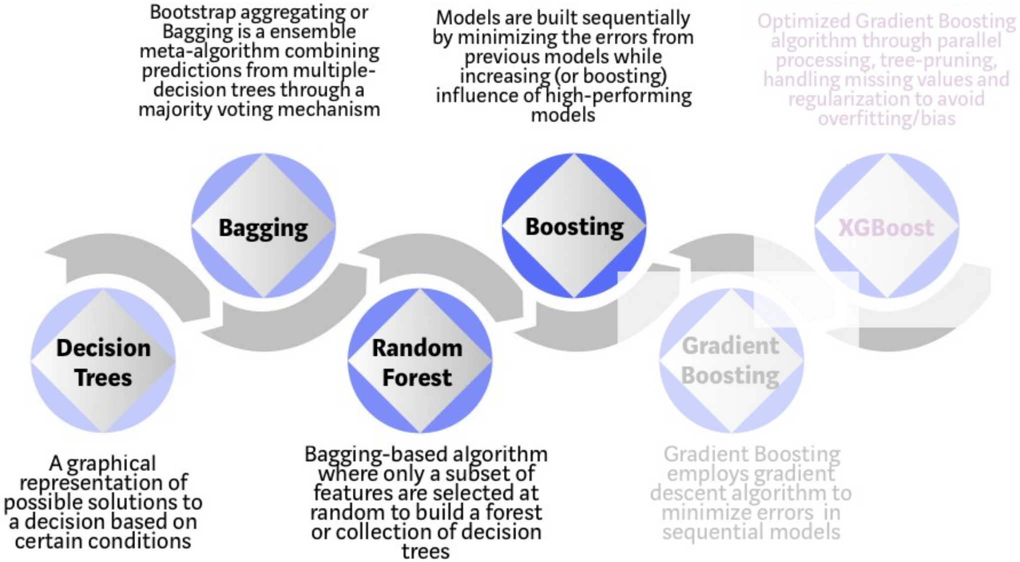
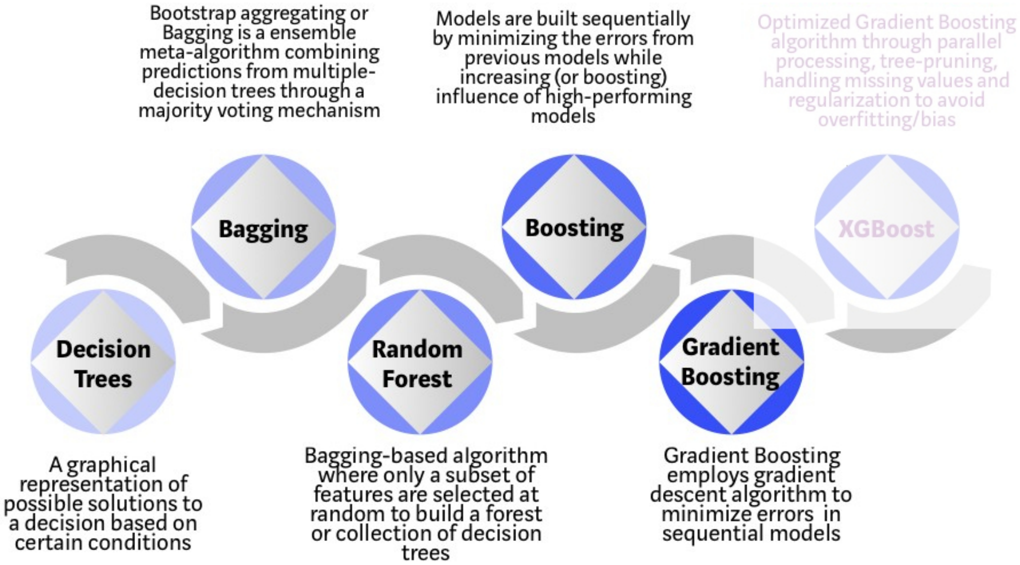
1. Each voting tree gets its own sample of data.
2. At each tree split, a random sample of features is drawn, only those features are considered for splitting.
3. For each tree, error rate is computed using data outside its bootstrap sample.

XGBoost Ingredients: Boosting



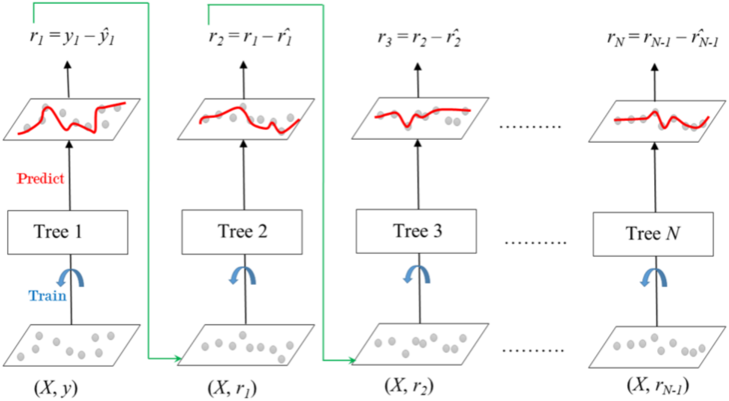
- works by sequentially adding predictors to an ensemble – fits the new predictor to the residual errors made by the previous predictor to gradually improve the model.

XGBoost Ingredients: Gradient Boosting



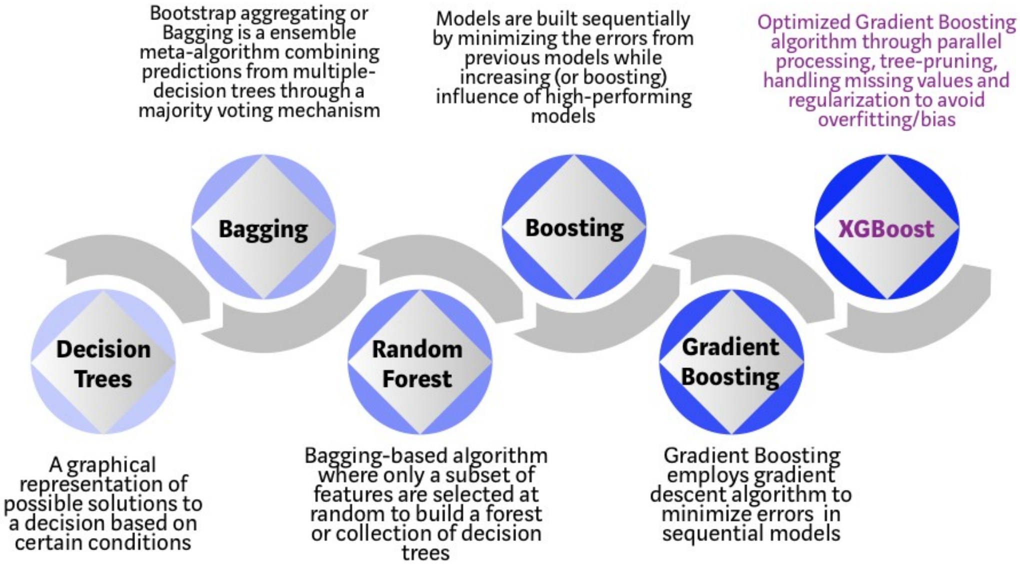
Gradient Boosting Machines

- 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

Complicated in Theory, Easy in practice

```
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)
```

- See more detailed examples/explanation in the "XGBoost Explained" reading, and this week's example code notebook.

Early Stopping with Validation Set

- Early stopping is an elegant regularization technique, used in xgboost and in neural nets:
  - gradually train the model gradients while checking fit in a held-out validation set.
    - for xgboost, this means adding more layers of trees to fit the residuals.
  - when model starts overfitting, stop training.

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  - when model starts overfitting, stop training.
- Requires user to specify two additional parameters:
  - **eval_set** = validation set (separate from training set and test set)
  - **early_stopping_rounds**: stop training if we have done this many epochs without improving validation set performance.

```
from sklearn.model_selection import train_test_split
X_val_train, X_test, y_val_train, y_test = train_test_split(X, y)
X_train, X_val, y_train, y_val = train_test_split(X_val_train, y_val_train)
```

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```
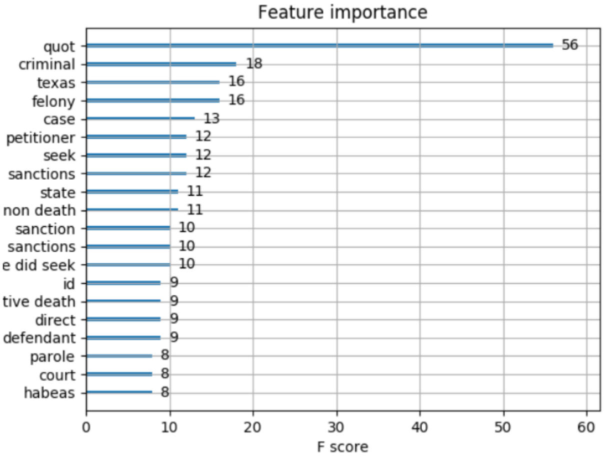

```
from xgboost import XGBClassifier
xgb = XGBClassifier(eval_set = [X_val, y_val], early_stopping_rounds=10)
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
balanced_accuracy_score(y_test, y_pred)
```

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. (will return to this in week 9)

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Response Essays

First Response Essay due Thursday

- Critically read and review an application paper.
- 300 words is the minimum for a passing grade (3+) but 500+ words would be expected for high grade (7+).
- Please anonymize your submission – put your name in the filename, but not anywhere in the file. Submit as TXT or PDF.

What can I write about?

Any "Applications" reading from weeks 1 through 5:

1. Goldin and Rouse 2000, Orchestrating impartiality? The impact of blind auditions on female musicians.
2. Bertrand and Mullainathan 2004, Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination
3. Glover, Pallais, and Pariente, Discrimination as a self-fulfilling prophecy
4. Chang et al, The mixed effects of online diversity training.
5. Kermani and Wong, Racial disparities in housing returns
6. Strittmatter and Wunsch, The gender pay gap revisited with big data: Do methodological choices matter?
7. Blumenstock, Cadamuro, and On, Predicting poverty and wealth from mobile phone metadata
8. Bonica, Inferring Roll-Call Scores from Campaign Contributions using Supervised Machine Learning
9. Ash and MacLeod, Mandatory retirement reforms for judges improved performance on U.S. state supreme courts
10. Ash, Chen, and Naidu, Ideas Have Consequences: The Impact of Law and Economics on American Justice
11. Bansak, Ferwerda, Hainmueller, Dillon, Hangartner, Lawrence, and Weinstein, Improving refugee integration through data-driven algorithmic assignment.
12. Osnabruegge, Ash, and Morelli, "Cross-Domain Topic Classification for Political Texts"
13. Katz, Bommarito, and Blackman, "A general approach for predicting the behavior of the Supreme Court of the United States."

Or another article applying tools from one of the first topics (machine learning, causal inference with linear regression, fixed effects models, or classification). Please confirm with me by email by tonight.

What to think about

<u>**Questions to ask in reading responses**</u>

1. What is the research question?
2. What is interesting about the data? Is it the right dataset to answer the research question?
3. Did they provide sufficient visuals and descriptive statistics to provide trust in the data and its usefulness for the stated purpose?
4. What is the goal of the data analysis?
   a. What are they trying to measure?
   b. What are they trying to predict or learn?
5. Given the answer to #4, is the right model being used? What other models could they have tried?
6. Did they provide validation that the model is delivering on the stated goals (#4)?
7. How were the model predictions/statistics used in a social-science analysis? What results seemed incomplete or non-robust?
8. Did they answer the research question (#1)? Highlight limitations and open questions.

- Annotated examples from previous years are available here: `http://bit.ly/BRJ_essay-examples`.

Discussion: Breakout Rooms (rest of class)

- Discuss "Biased algorithms are easier to fix than biased people" by Sendhil Mullainathan in *New York Times* (`bit.ly/nyt-bias`).
  - Think of another task where fixing biases in an algorithm is probably easier than fixing it in humans.
  - Can you think of the opposite case — a task where fixing biases in humans is easier than fixing biases in algorithms?
  - Has your attitude to this article changed at all since the first week of class?
- put your answers in a shared doc and paste a link here: `https://padlet.com/eash44/p6ypvf4uodlgu7jz`