Building a Robot Judge: Data Science for Decision-Making

3. Machine Learning Essentials

Instructions before we begin:
(1) Turn on video and set audio to mute
(2) In Participants panel, set zoom name to "Full Name, School / Degree"
(ex: "Leon Smith, ETH Data Science Msc")
(3) If this is your first lecture, say "hi" in the chat

Q&A Page

https://padlet.com/eash44/ja1iim3i1ghcc0r5

Course Exam Info

- For those not doing a project, there is a take-home exam distributed in late December.
  - Questions will be based on the slides.
  - Will distribute practice questions beforehand.

Discrimination: Evidence

- Goldin and Rouse (2000):
  - natural experiment: orchestras moved to blind auditions.
  - positive effect: blind auditions helped women get positions in the orchestra.
- Bertrand and Mullainathan (2004):
  - Randomized otherwise equivalent resumes to have African-American or White sounding names.
  - 50% gap in callback rate for black-sounding names

Limitations of these studies? Ways to improve them?

Outline

Essentials

Regression / Regularization

Activity on Causal Graphs

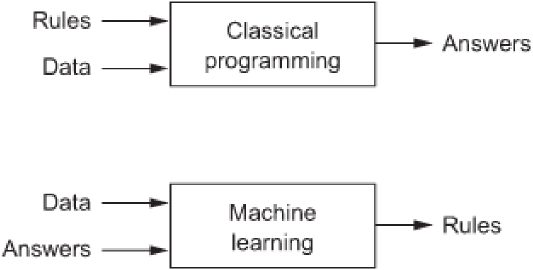
Binary Classification

Applications

Learning Objectives

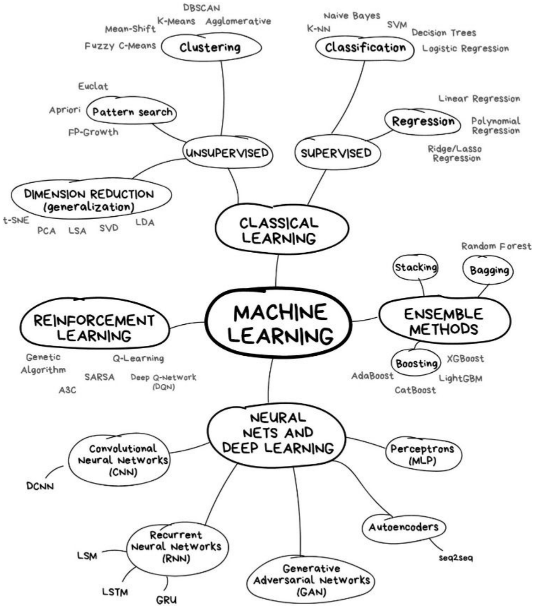
1. **Implement and evaluate machine learning pipelines.**
   - **Evaluate (find problems in) existing machine learning pipelines.**
   - **Design a pipeline to solve a given ML problem.**
   - **Implement some standard pipelines in Python.**
2. Implement and evaluate causal inference designs.
3. Understand how (not) to use data science tools (ML and CI) to support expert decision-making.

What is machine learning?

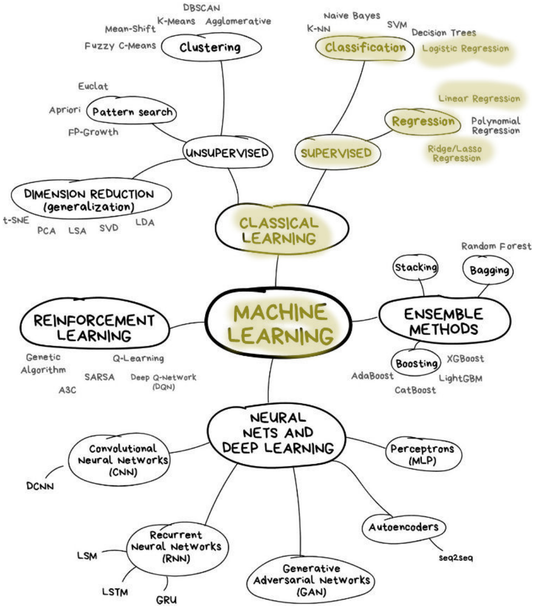


- In classical computer programming, humans input the rules and the data, and the computer provides answers.
- In machine learning, humans input the data and the answers, and the computer learns the rules.

The Machine Learning Landscape



What we will do today



A Machine Learning Project, End-to-End

Aurelien Geron, *Hands-on machine learning with Scikit-Learn, Keras, & TensorFlow*, Chapter 2:

1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data to gain insights.
4. Prepare the data for Machine Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.
8. Launch, monitor, and maintain your system.

Three Types of (Standard) Machine Learning Problems

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

- **Binary classification**: two choices, normalized to zero and one.
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- **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 type of ML Problem is this?

- Based on defendant characteristics and the facts of the case, predict which charges the prosecutor will bring:
  - third degree murder (manslaughter)
  - second degree murder (crime of passion)
  - first degree murder (premeditated)

  {binary classification, regression, or multinomial classification}
- **private zoom chat answer to claudia (30 secs)**

What do ML Algorithms do? Minimize a cost function

What do ML Algorithms do? Minimize a cost function

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

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

  - 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 $h(x;\theta) = x_i'\theta$ and minimizes the mean squared error (MSE)

$$\min_{\hat{\theta}} \frac{1}{n_D} \sum_{i=1}^{n_D} (x_i'\hat{\theta} - y_i)^2$$

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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).

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

- The partial derivative for feature j is

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

  - $\rightarrow$ estimates how changing θ_j would reduce the error across the whole dataset.

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

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

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

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

  - η = learning rate
- keep nudging until convergence.

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- ***Stochastic* gradient descent (SGD):** Compute gradient for single random instance (rather than whole dataset) at each iteration. Much faster, still works.

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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  - 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.
- Cross-validation is less common in deep learning, where training multiple models is too computationally expensive.
  - instead, use dropout and early stopping (week 7).

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)
- mean absolute error (MAE, $\sum |\hat{y}(\theta) - y|$) is less sensitive to outliers.

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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 and in week 5).

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Activity on Causal Graphs

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Regression models $\leftrightarrow$ Continuous outcome

- If the outcome is continuous (e.g., Y = tax revenues collected, or criminal sentence imposed in months of prison):

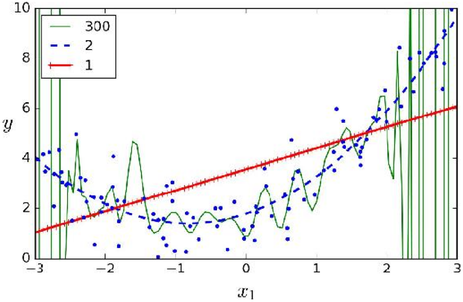

Figure 4-14. High-degree Polynomial Regression

- Need a regression model. Problems with OLS:
  - tends to over-fit training data.
  - cannot handle multicollinearity.

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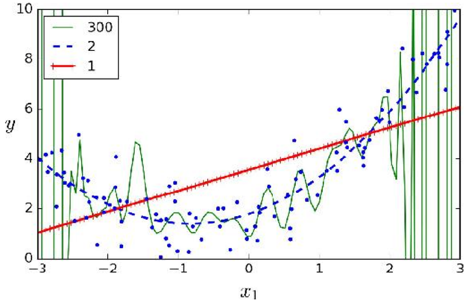

Figure 4-14. High-degree Polynomial Regression

- Machine learning models are evaluated by the fit in held-out data (the test set)
  - "Regularization" refers to ML model training methods designed to reduce/prevent over-fitting of the training set
  - (and hopefully better fit in the test set).

Regularization

- Minimizing the loss L directly usually results in over-fitting. It is standard to add regularization:

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

  - $R(\theta)$ is a "regularization function" or "regularizer", designed to reduce over-fitting.
  - λ is a hyperparameter where higher values increase regularization.

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"Ridge" and "Lasso" penalize larger coefficients, shrinking them toward zero:

- Ridge (or L2) penalty:

$$R_2 = \|\theta\|_2^2 = \sum_{j=1}^{n_x} (\theta_j)^2$$

  - also helps select between collinear predictors.
- Lasso (or L1) penalty:

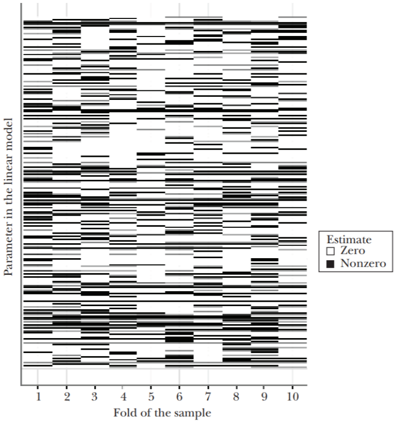
$$R_1 = \|\theta\|_1 = \sum_{j=1}^{n_x} |\theta_j|$$

  - also performs feature selection and outputs a sparse model.

Does lasso pick the “true” model?

Lasso prediction of house prices with 150 variables – which variables are “selected” (non-zero coefficients) by lasso, in ten models trained on separate data subsamples (Mullainathan and Spiess 2017):

Selected Coefficients (Nonzero Estimates) across Ten LASSO Regressions



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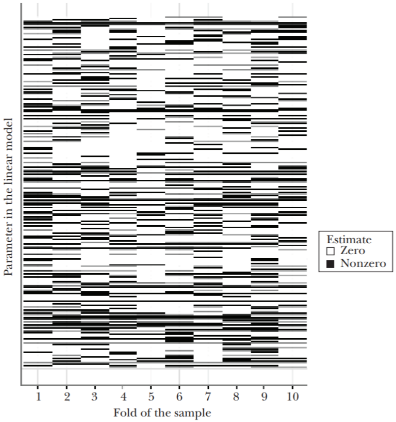

- The set of lasso-selected variables changes across folds in the data
- $\rightarrow$ Lasso does not pick the "correct" predictors.
  - It just learns the correct $\hat{h}(X)$
  - when predictors are correlated with each other, they are substitutable.

Elastic Net = Lasso + Ridge

The Elastic Net cost function is:

$$
\begin{aligned}
L(\theta) &= \mathrm{MSE}(\theta) + \lambda_1 R_1 + \lambda_2 R_2 \\
&= \mathrm{MSE}(\theta) + \lambda_1 \sum_{j=1}^{n_x} |\theta_j| + \lambda_2 \sum_{j=1}^{n_x} (\theta_j)^2
\end{aligned}
$$

- λ_1, λ_2 = strength of L1 (Lasso) penalty and L2 (Ridge) penalty, respectively.

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In scikit-learn, e-net penalties are parametrized as "`alpha`" = total penalty, and "`l1_ratio`" = proportion of penalty to L1.

```
from sklearn.linear_model import ElasticNet
enet = ElasticNet(alpha=2.0, l1_ratio = .75) # L1 = 1.5, L2 = 0.5
enet.fit(X,y)
```

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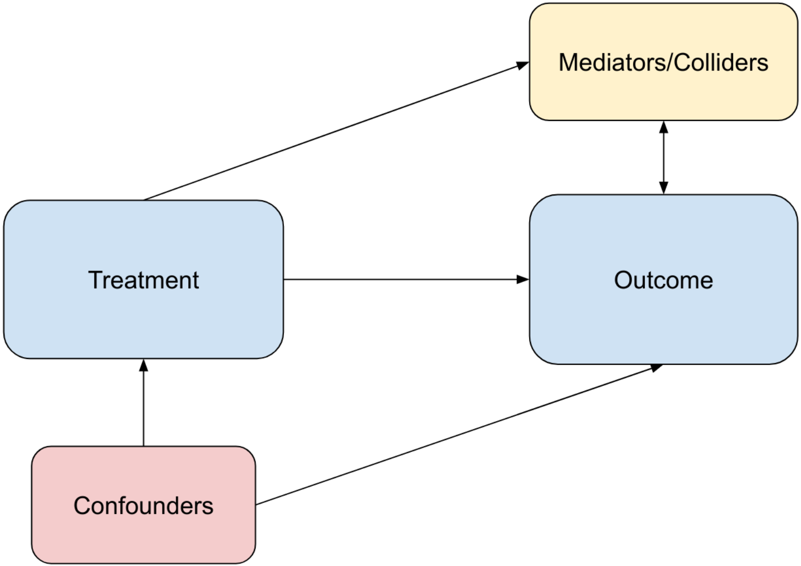
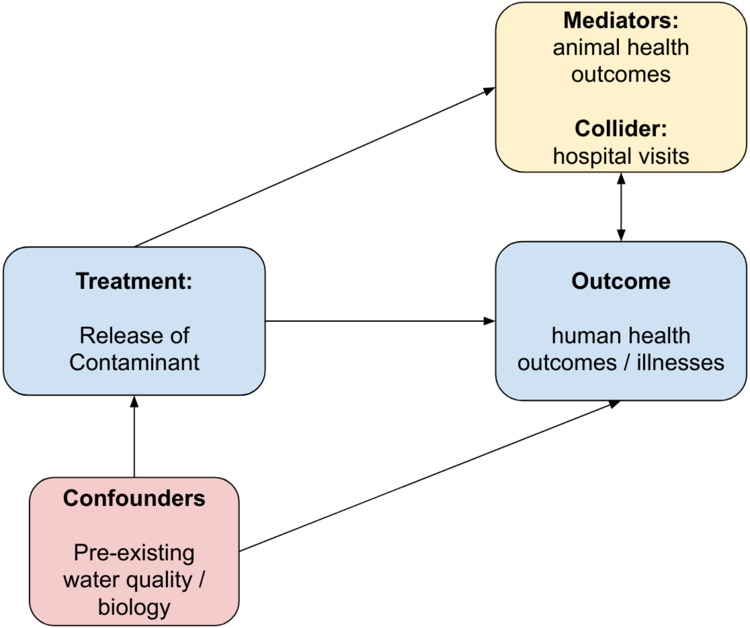
Causal Graphs: Review



Causal Graph Example: Pollution of a River



Activity: Practice with Causal Graphs

- Think of an example causal inference question:
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  - a policy you are interested in
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- Link to causal graph template: `http://bit.ly/BRJ-W5A2a`
  - make a copy, fill it in
  - make public and paste link into padlet (`https://padlet.com/eash44/vngufrdr5gydibx`)

Breakout Rooms: Share and Check Causal Graphs

- 3 minutes each, in alphabetical order by first name:
  - say hello and introduce yourself.
  - introduce your causal graph
  - others ask questions / provide feedback

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Binary Outcome $\leftrightarrow$ Binary Classification

- Binary classifiers try to match a boolean outcome $y \in \{0, 1\}$.
  - The standard approach is to apply a transformation (e.g. sigmoid/logit) to normalize $\hat{y} \in [0, 1]$.
  - Prediction rule is 0 for $\hat{y} < .5$ and 1 otherwise.

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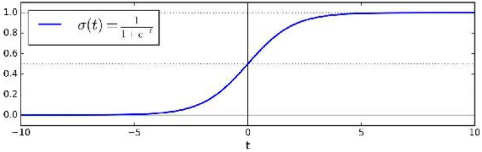
  - Prediction rule is 0 for $\hat{y} < .5$ and 1 otherwise.
- The binary cross-entropy (or log loss) is:

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

- 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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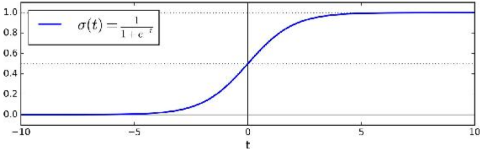

- Plugging into the binary-cross entropy loss gives the logistic regression cost objective:

$$\min_{\theta} \sum_{i=1}^{n_D} -y_i \log(\text{sigmoid}(\boldsymbol{x}_i \cdot \theta)) - [1 - y_i] \log(1 - \text{sigmoid}(\boldsymbol{x}_i \cdot \theta))$$

  - does not have a closed form solution, but it is convex (guaranteeing that gradient descent will find the global minimum).

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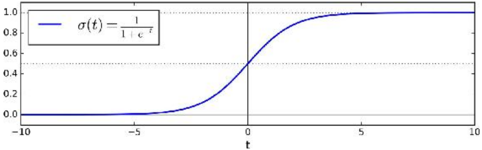

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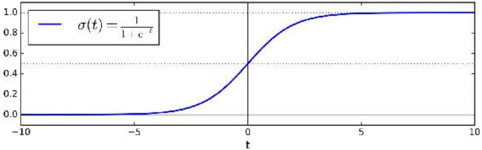

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- Like linear regression, logistic regression can be regularized with L1 or L2 penalties.

```
from sklearn.linear_model import LogisticRegression
logit = LogisticRegression(penalty='l2', C = 2.0) # lambda = 1/2
logit.fit(X,y)
```

A **Confusion Matrix** is 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.

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

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

- Cell values give counts in the test set.

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

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

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

A **Confusion Matrix** is 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.

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

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

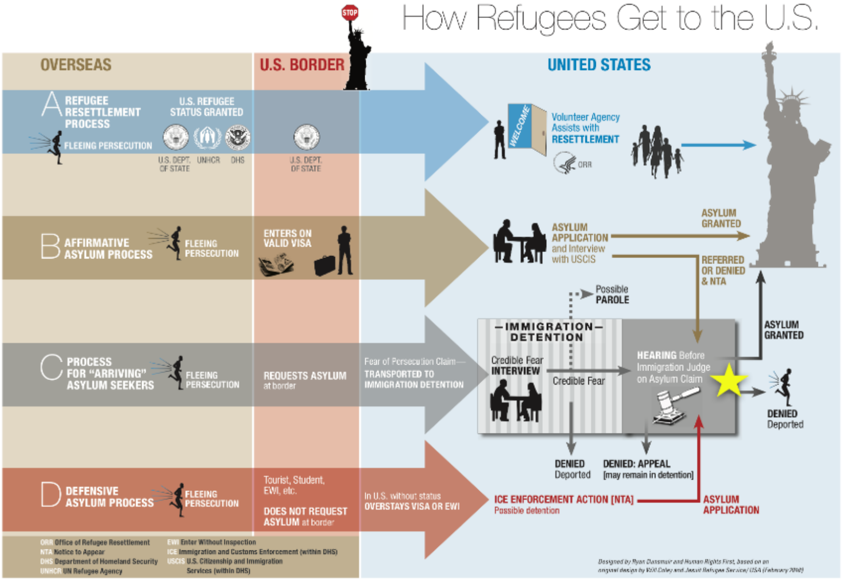
- Precision decreases with false positives. "When I guess this outcome, I tend to guesses correctly."

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

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

Outline

Asylum in the U.S.



Source: rcusa.org.

Dunn, Sagun, Sirin, and Chen (2017): Asylum Courts

- Data:
  - universe of asylum court cases, 1981-2013
  - 492,903 decisions, 336 courts, 441 judges

Dunn, Sagun, Sirin, and Chen (2017): Asylum Courts

- Data:
  - universe of asylum court cases, 1981-2013
  - 492,903 decisions, 336 courts, 441 judges
- High stakes: denial of asylum results in deportation.
- Average grant rate: 35%.
- What type of ML problem is this?

Predicting U.S. Asylum Court Decisions

		Predicted	
		Denied	Granted
True	Denied	195,223	65,798
	Granted	73,269	104,406

Accuracy = 68.3%, F1 = 0.60

- Prediction App: `https://floating-lake-11821.herokuapp.com/`
  - predictions made using logistic regression with L2 regularization, penalty selected by cross-validation grid search.

Judge Identity is Most Predictive Factor

Model	Accuracy	ROC AUC
Judge ID	0.71	0.74
Judge ID & Nationality	0.76	0.82
Judge ID & Opening Date	0.73	0.77
Judge ID & Nationality & Opening Date	0.78	0.84
Full model at case completion	0.82	0.88

- Predictions from random forest classifier, with parameters selected by cross-validated grid search.
  - Training/test split 482K/120K.

Judge Variation in Predictability

- Some judges are highly predictable, always granting or rejecting.
  - suggests they use heuristics or stereotypes rather than considering cases carefully.

Judge Variation in Predictability

- Some judges are highly predictable, always granting or rejecting.
  - suggests they use heuristics or stereotypes rather than considering cases carefully.
- There is significant variation in predictability by judge, conditional on grant rate.
  - suggests disagreement about circumstances contributing to asylum decision.

What type of ML Problem is this? (Bonica 2018)

http://bit.ly/BRJ_bonica

Abstract: *This article develops a generalized supervised learning methodology for inferring roll-call scores from campaign contribution data. Rather than use unsupervised methods to recover a latent dimension that best explains patterns in giving, donation patterns are instead mapped onto a target measure of legislative voting behavior. Supervised models significantly outperform alternative measures of ideology in predicting legislative voting behavior. Fundraising prior to entering office provides a highly informative signal about future voting behavior. Impressively, forecasts based on fundraising as a nonincumbent predict future voting behavior as accurately as in-sample forecasts based on votes cast during a legislator's first 2 years in Congress. The combined results demonstrate campaign contributions are powerful predictors of roll-call voting behavior and resolve an ongoing debate as to whether contribution data successfully distinguish between members of the same party.*

- **private zoom chat to Claudia**

Vaccine Allocation, Age, and Race (rest of class)

- Breakout groups: Noah Smith's article, "Vaccine Allocation, Age, and Race
  - Summarize the main points, and relate them to our discussions in class.
  - Think of another policy/decision with similar issues, explain.
- Task:
  - Discuss your ideas in your group
  - write them down in a shareable doc
  - post a link in the padlet: `https://padlet.com/eash44/ijayp3e8r5zfrxtg`.