Sequencing Legal DNA

NLP for Law and Political Economy

4. Supervised Learning with Text

Reminder: Assignment 1 Due by Wednesday

- Two reading response essays, one code replication exercise, a problem set solution, or the hybrid assignment (one essay and answers to four problem set questions).
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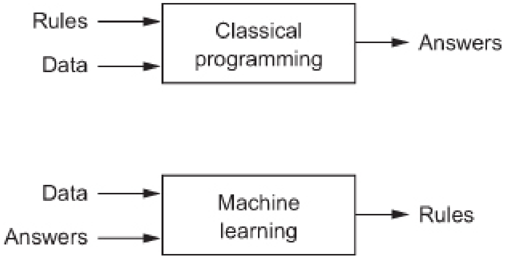
- Essays will be posted (anonymously) on the forum:
  - please vote on some of your classmates' essays, and comment on at least one (before next week's class).

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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- y is one-dimensional ($n_y = 1$), x is low-dimensional ($n_x \ll n_D$).
- estimate a low-dimensional **causal parameter** ρ using

$$y_i = \alpha_i + x_i \cdot \rho + \epsilon_i$$

where i indexes over documents, α_i includes control variables (and fixed effects), $\cdot$ is dot product, and ϵ_i is the error residual.

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  that predicts $\boldsymbol{y}$ given covariates $\boldsymbol{x}$.
- if we collected more data on $\boldsymbol{x}$, we could predict the associated $\hat{y}$.
- but $h(\cdot)$ does not provide a *counterfactual prediction* – that is, how the outcome would change if $\boldsymbol{x}$'s were exogenously shifted.

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4. Empirical analysis
   - Produce statistics or predictions with the trained model.
   - **Answer the research question.**

What do ML Algorithms do? Minimize a cost function

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

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

  - n_D, the number of rows/observations
  - x, the feature set, with row x_i
  - y, the set of outcomes, with item y_i
  - $f(x_i; \theta) = \hat{y}$ 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 corpus-wide average loss is

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

  - $\rightarrow$ treats the data as constants; parameters determine the loss.
- The estimated parameter matrix θ solves

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

OLS Regression is Machine Learning

- OLS assumes the functional form $f(x;\theta) = x_i'\theta$ and minimizes the MSE

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

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

- This minimand has a closed form solution

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

- But most machine learning models do **not** have a closed form solution.

How do ML Algorithms Work? Gradient Descent

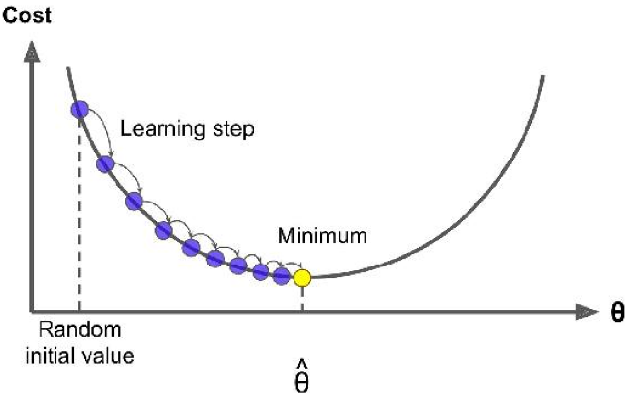

Figure 4-3. Gradient Descent

- Gradient descent measures the local gradient of the error function, and then steps in that direction.
  - Once the gradient equals zero, you have reached a minimum.

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

- The partial derivative of MSE for feature j is

$$\frac{\partial \text{MSE}}{\partial \theta_j} = \frac{2}{m} \sum_{i=1}^{n} (\boldsymbol{x}_i' \hat{\theta} - y_i) x_i^j$$

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

$$\nabla_\theta \mathrm{MSE} = \begin{bmatrix} \frac{\partial \mathrm{MSE}}{\partial \theta_0} \\ \frac{\partial \mathrm{MSE}}{\partial \theta_0} \\ \vdots \\ \frac{\partial \mathrm{MSE}}{\partial \theta_j} \end{bmatrix} = \frac{2}{m} \boldsymbol{X}' (\boldsymbol{X}' \theta - \boldsymbol{y})$$

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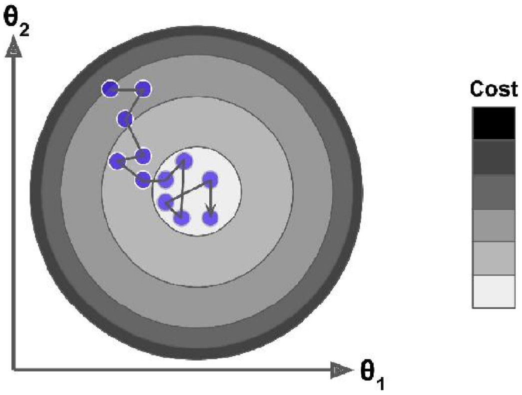
- Gradient descent nudges θ against the gradient (the direction that reduces MSE):

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

  - η = learning rate

Stochastic Gradient Descent

- SGD picks a random instance in the training set and computes the gradient only for that single instance.



- Much faster to train, but bounces around even after it is close to the minimum.
  - Compromise: mini-batch gradient descent, selects a sample of rows (a "mini-batch") for gradient compute.

Training and Testing

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  - 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.

Data Prep for Machine Learning

- See Geron Chapter 2 for pandas and sklearn syntax:
  - imputing missing values.
  - feature scaling (often helpful/necessary for ML models to work well)
  - encoding categorical variables.

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  - encoding categorical variables.
- Best practice:
  - **reproducible data pipeline**.
  - if you want a "clean" evaluation in the test set, you have to **do data prep in the training set**.

Scikit-Learn Design Overview

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  - Estimation is performed by `fit()` method.
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  - **Non-proliferation of classes:** Use native Python data types; existing building blocks are used as much as possible.
  - **Sensible defaults:** Provides reasonable default values for hyperparameters – easy to get a good baseline up and running.

Use Cross-Validation During Model Training

- Within the training set:
  - Use `cross_val_score` method to get model performance across subsets of data.
  - Use `GridSearchCV` or `RandomizedSearchCV to automate search over parameter space.`
- Find the best hyperparameters for out-of-fold prediction in the training set.
  - then evaluate model performance in the test set.

Regression models ↔ 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.

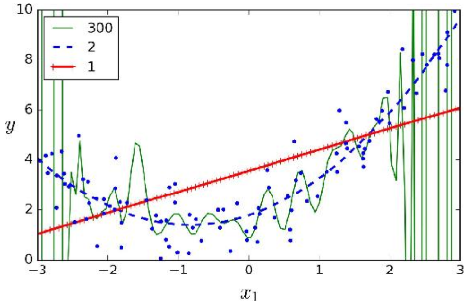

Figure 4-14. High-degree Polynomial Regression

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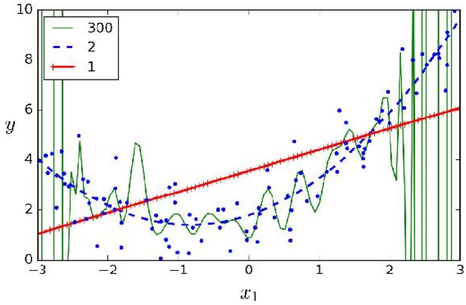

Figure 4-14. High-degree Polynomial Regression

- 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:

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

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

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  - λ is a hyperparameter where higher values increase regularization.
- For example:
  - "Ridge" penalty:
$$R_2 = \|\theta\|_2^2 = \sum_{j=1}^{n_x} (\theta_j)^2$$
  - "Lasso" penalty:
$$R_1 = \|\theta\|_1 = \sum_{j=1}^{n_x} |\theta_{j]}|$$

Elastic Net = Lasso + Ridge

- The Elastic Net cost function is:

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

  - λ_1 is a hyperparameter setting the strength of the L1 (Lasso) penalty – automatically performs feature selection and outputs a sparse model.

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\end{aligned}
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  - λ_1 is a hyperparameter setting the strength of the L1 (Lasso) penalty – automatically performs feature selection and outputs a sparse model.
  - λ_2 is a hyperparameter setting the strength of the L2 (Ridge) penalty – shrinks coefficients toward zero and helps select between collinear predictors.

Scaling while maintaining sparsity

- Regularization penalties are designed to work with scaled data.
  - An important feature of text data is sparsity, which is lost when taking out the mean:

$$\tilde{x}_i = \frac{x_i - \bar{\boldsymbol{x}}}{\mathrm{SD}[\boldsymbol{x}]}$$

- Solution:

$$\tilde{x}_i = \frac{x_i}{\mathrm{SD}[\boldsymbol{x}]}$$

  - in sklearn, use **`StandardScaler(with_mean=False)`**.
  - *Note: should not include validation/test observations in calculating SD.*

Selecting Elastic Net Hyperparameters

- Elastic net hyperparameters should be selected to optimize out-of-sample fit.
- "Grid search" scans over the hyperparameter space ($\lambda_1 \geq 0$,$\lambda_2 \geq 0$), computes out-of-sample MSE for all pairs (λ_1, λ_2), and selects the MSE-minimizing model.

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- In general, mean squared error (MSE) should be used as the metric for selecting regression models.

Evaluating Regression Models: R^2

- Mean squared error is good for comparing regression models, but the units depend on the outcome variable and therefore are not interpretable.
  - Better to use R^2 in the test set.
  - MSE and R^2 provide the same ranking of models.

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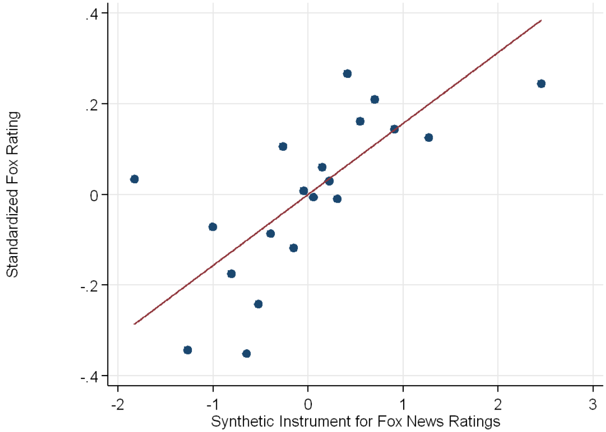
  - Better to use R^2 in the test set.
  - MSE and R^2 provide the same ranking of models.
- If you do not want to lose data, you can use cross-validation to get evaluation metrics for every fold in the data:
  - split data into K folds, e.g. 5.
  - for each fold $k \in \{1, 2, ..., K\}$, train and tune model in rest of data $-k$, and evaluate R^2 in k.
  - Report mean and s.d. of R^2 across folds.

Evaluating Regression Models: Binscatter Plots

- Binscatters (e.g. seaborn.regplot) provide visual evidence of regression model performance: Plot y against $\hat{y}$ in the test set:



Sample from Ash and Labzina (2019). $R^2 = .03$.

Binary Outcome $\leftrightarrow$ Binary Classification

- Binary classifiers try to match a boolean outcome $y \in \{0, 1\}$.
- Simplest linear model is

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that is, choose one if positive and zero if negative.
- Better option: use a sigmoid transformation
$$\hat{y} = \text{sigmoid}(\boldsymbol{x} \cdot \theta)$$
with
$$\text{sigmoid}(a) = \frac{1}{1 + \exp(-a)}$$
  - Then $\hat{y} \in [0, 1]$ can be interpreted as the predicted probability of class 1 given $\boldsymbol{x}$.

Training Classifiers

- Better classifiers $\leftrightarrow$ more accurate in held-out test set.

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- Better classifiers $\leftrightarrow$ more accurate in held-out test set.
  - as above, tune a model's hyperparameters in the training set, then evaluate in the test set.
  - Can use MSE as cost function in binary models, but other cost functions have better performance.

Binary cross-entropy (logistic loss)

- Assume $y \in \{0, 1\}$ and $\hat{y} \in [0, 1]$ (e.g., by sigmoid transformation).
- Prediction rule is 0 for $\hat{y} < .5$ and 1 otherwise.

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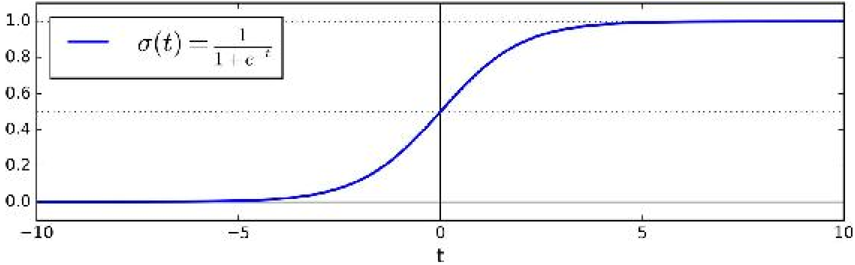
- Logistic loss:

$$L(\theta) = -y \log \hat{y}(x, \theta) - [1 - y] \log(1 - \hat{y}(x, \theta))$$

Logistic Regression is for Classification

- Logistic "regression" computes a weighted sum of the input features to predict the output.
  - But rather than output the sum directly, it transforms the sum using the logistic function:

$$\hat{y} = \Pr(y_i = 1) = \frac{1}{1 + \exp(-\theta' x)})$$



- The prediction $\hat{Y} \in \{0, 1\}$ is determined by whether $\hat{p} \gtrless .5$.
- Can be regularized with L1 or L2 penalties.

Logistic Regression Cost Function

- The log loss

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

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

Logistic Regression Cost Function

- The log loss

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

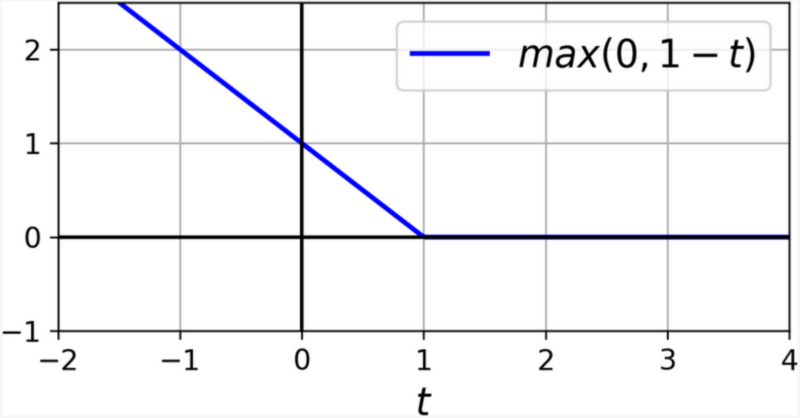
  does not have a closed form solution
- but it is convex, so gradient descent will find the global minimum.
- Just like linear models, logistic can be regularized with L1 or L2 penalties, e.g.:

$$L_2(\theta) = \mathrm{L}(\theta) + \lambda_2 \sum_{j=1}^{n_x} \theta_j^2$$

Hinge Loss (used in SVM)

HINGE LOSS

The function *max*(0, 1 – *t*) is called the *hinge loss* function (see the following image). It is equal to 0 when $t \geq 1$. Its derivative (slope) is equal to –1 if $t < 1$ and 0 if $t > 1$. It is not differentiable at $t = 1$, but just like for Lasso Regression (see "Lasso Regression"), you can still use Gradient Descent using any *subderivative* at $t = 1$ (i.e., any value between –1 and 0).



Confusion Matrix

- A confusion matrix is a nice way to visualize classifier performance:

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

- The values in the table give counts in the evaluation set.

Precision and Recall

		True Class	
		Positive	Negative
Predicted Class	Positive	# True Positives	# False Positives
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$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} = \text{Row Mean}$$

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- **Precision decreases with false positives.**
- **Recall decreases with false negatives.**
- **Note:** here, we computed precision and recall for the positive class. Can do the same for the negative class (symmetrically).

Accuracy vs. F1 Score

- If labels are (almost) balanced, then accuracy (share correct predictions) is a decent metric.
  - If not (say 90% in one category), accuracy will be uninformative/misleading.

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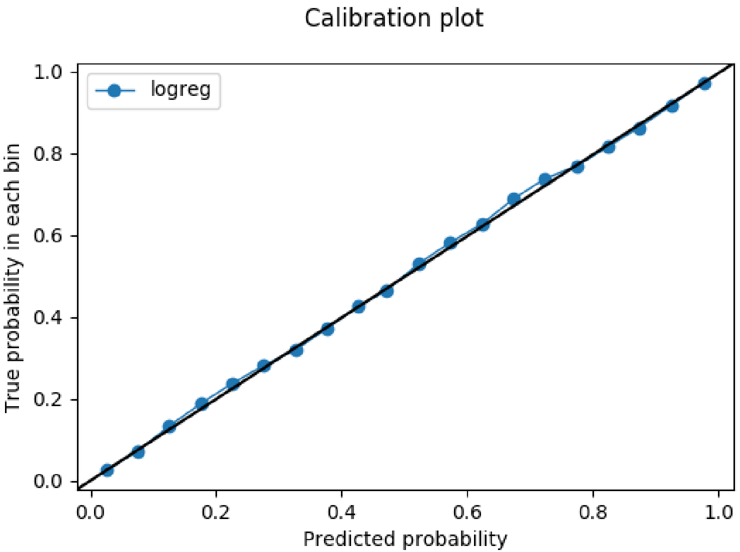
- If labels are (almost) balanced, then accuracy (share correct predictions) is a decent metric.
  - If not (say 90% in one category), accuracy will be uninformative/misleading.
- F_1 score provides a combined metric for use with imbalanced data, the harmonic mean of precision and recall:

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

  - requires decent accuracy 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):



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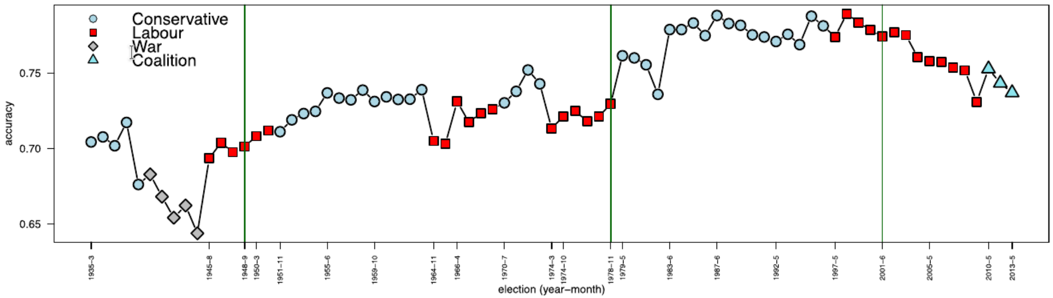
- Machine Learning Problem:
  - Corpus D = 3.5M U.K. parliament speeches, 1935-2013.
  - Label Y = party of speaker (Conservative or Labour)
- Analysis:
  - In years that classifier is more accurate, speech is more polarized.

Polarization in U.K. Parliament

Peterson and Spirling (*Political Analysis* 2018)



- Accuracy of party prediction over time.

Polynomial Features don't work in NLP

- There could be important pair-wise interactions or non-linear effects of the features.
- But computing polynomial features in NLP problems is (usually) computationally intractable:
  - for n_x features, a degree-2 polynomial transformation gives $2n_x + (n_x - 1)^2$ features.
  - e.g., with 10K features, transformation produces 100M polynomial features.

The Kernel Trick

- Consider two vectors $\boldsymbol{a}$ and $\boldsymbol{b}$ with dot product $\boldsymbol{a} \cdot \boldsymbol{b}$.
- Let $\phi(\cdot)$ be a transformation of the vectors which increases dimensionality, satisfying certain properties (Mercer 1909).
  - E.g. a degree-2 polynomial transformation:

$$\phi(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}) = \begin{bmatrix} x_1^2 \\ \sqrt{2}x_1x_2 \\ x_2^2 \end{bmatrix}$$

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  - e.g., for the quadratic transformation, $\phi(\boldsymbol{a}) \cdot \phi(\boldsymbol{b}) = (\boldsymbol{a} \cdot \boldsymbol{b})^2$.
- This "kernel trick" means that some classifiers (notably SVM) can use the predictive information from feature interactions without increasing dimensionality.

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 topic labels in speeches or articles

Multiple Classes: Setup

- The outcome $y_i \in \{1, ..., k, ..., n_y\}$ output classes, with one-hot vector representation
$$\boldsymbol{y}_i = \{\mathbf{1}[y_i = 1], ..., \mathbf{1}[y_i = n_y]\}$$

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$$\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x}, \theta)$$
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- Our machine classifier outputs a vector of probabilities
$$\hat{\boldsymbol{y}} = \{\hat{y}^1, ..., \hat{y}^{n_y}\}, \hat{y}^k \in [0, 1] \; \forall k$$
and for prediction/decision, selects the highest-probability class:
$$\tilde{y} = \arg\max_k \hat{y}_{[k]}$$

Softmax Transformation

- Since $\hat{y}$ are probabilities, we normally want to ensure they are non-negative and sum to one.
- Standard approach: transform the score vector using the softmax function:

$$\mathrm{softmax}(\boldsymbol{a})_{[k]} = \frac{\exp(\boldsymbol{a}_{[k]})}{\sum_l \exp(\boldsymbol{a}_{[l]})}$$

  the multi-class generalization of sigmoid$(\cdot)$.
- In our notation:

$$\hat{y}_{[k]}(\boldsymbol{x}, \theta) = \frac{\exp(f_k(\boldsymbol{x}, \theta))}{\sum_l \exp(f_l(\boldsymbol{x}, \theta))}$$

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 the dissimilarity between the true label distribution $\boldsymbol{y}$ and the predicted label distribution $\hat{\boldsymbol{y}}$.
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  - measures the dissimilarity between the true label distribution $\boldsymbol{y}$ and the predicted label distribution $\hat{\boldsymbol{y}}$.
  - convex, so gradient descent will find the global minimum.
- Usually there is just one true class ($y = 1$ for one class, and zero for others). So this simplifies to

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

  where k^* is the true class.
  - Rewards putting higher probability on the true class, ignores distribution of probabilities on other classes.

Multinomial Logistic Regression

- Logistic can be generalized to multiple classes.
  - For a given data point i, multinomial logistic computes a score $f_k(\boldsymbol{x}_i)$ for each class k,
$$f_k(\boldsymbol{x}_i) = \theta_k' \boldsymbol{x}_i$$
  - With n_x features and n_y output classes, there is a $n_y \times n_x$ parameter matrix Θ, where the parameters for each class are stored as rows.

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  - With n_x features and n_y output classes, there is a $n_y \times n_x$ parameter matrix Θ, where the parameters for each class are stored as rows.
- Using the scores, probabilities for each class are computed using the softmax function
$$\hat{y}_k(\boldsymbol{x}_i) = \Pr(y_i = k) = \frac{\exp(\theta'_k \boldsymbol{x}_i)}{\sum_{l=1}^{n_y} \exp(\theta'_l \boldsymbol{x}_i)}$$
  - And the prediction $y_i \in \{1, ..., n_y\}$ is determined by the highest-probability category.

Regularized Multinomial Logistic

- The corpus-wide categorical cross entropy is

$$\mathcal{L}(\theta) = \underbrace{-\frac{1}{n_D}}_{\text{negative}} \sum_{i=1}^{n_D} \sum_{k=1}^{n_y} \underbrace{\mathbf{1}[y_i = k]}_{y_i=k} \underbrace{\log(\hat{\boldsymbol{y}}_k(\boldsymbol{x}_i))}_{\text{log prob} y_i=k}$$

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- The L2-penalized logistic regression loss is

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

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

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).

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

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

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

Metrics for whole model

- **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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- **Micro-averaging**: Compute model-level sums for true positives, false positives, and false negatives; compute precision/recall from model sums.

$$\text{Precision} = \frac{\text{Total TP}}{\text{Total TP + Total FP}}, \text{Recall} = \frac{\text{Total TP}}{\text{Total TP + Total FN}}, F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

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- "**Weighted**": computed like macro-averaging, but classes are weighted by true frequency.

Multiple Continuous Outcomes

- What if we want to predict multiple continuous (non-categorical) outcomes?
  - e.g., want to predict the share of court case text across three categories: facts, law, and verdict.
  - or the share of speaking time used by each judge in oral argument

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  - e.g., want to predict the share of court case text across three categories: facts, law, and verdict.
  - or the share of speaking time used by each judge in oral argument
- Regression models (in particular, many of the regression models in scikit-learn) work fine in this case.
  - costs (e.g. MSE) are added up across outcome classes for each observation.

Cross-Domain (Transfer) Learning

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  - train a model in a big labeled dataset
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  - labeled data is scarce/expensive, so learn tasks on tons of unlabeled data.
  - BERT and GPT-2 are the big success stories in transfer learning.

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This paper takes the idea of transfer learning to the political science context.

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- 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
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  - Costs of using a pre-trained model (cross-domain learning) are moderate, assuming that one annotates a subset of documents for validation.

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  - generic dictionaries and cross-domain learning are moderate, as it requires that a dictionary/model already exists for the dimension of interest.

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- **Interpretability**: Do you understand what the model is doing?
  - dictionaries and annotation codebooks are easy to inspect.
  - topics produced by LDA are sometimes interpretable, sometimes not.

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- **Validatability**: Is the model classifying documents correctly?
  - dictionaries and topic models cannot be validated without hand-labeling of documents, which defeats the purpose.
  - supervised learning models on annotated data can be validated with machine learning metrics.

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  - also: 8 broader “topic domains” (external relations, freedom and democracy, political system, economy, welfare and quality of life, fabric of society, social groups, and no topic)

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- $n_x = 19,734$ features
  - compute tf-idf-weighted n-gram frequencies

Prediction Model

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Predict the CMP code in a held-out sample of manifesto corpus statements:

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  - test-sample accuracy = 0.54
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- 8-topic specification:
  - test-sample accuracy $= 0.64$
  - training-sample accuracy $= 0.76$
  - choosing randomly $==$ 0.125 accuracy, choosing most-frequent category would be correct 30% of the time.

	Economy	External Relations	Fabric of society	Freedom & Democracy	Political system	Social groups	Welfare & quality of life	No topic / Other	Total true
Economy	5270	93	131	40	301	254	1108	0	**7197**
External Relations	175	1207	137	83	85	49	209	1	**1946**
Fabric of society	269	107	1785	90	204	115	618	1	**3189**
Freedom and Democracy	102	60	135	631	219	35	177	0	**1359**
Political system	608	71	186	137	1255	65	542	1	**2865**
Social groups	493	51	185	29	111	1230	818	0	**2917**
Welfare and quality of life	1033	66	316	58	267	293	7138	0	**9171**
No topic / Other	58	6	37	9	34	7	55	3	**209**
Total predicted	**8008**	**1661**	**2912**	**1077**	**2476**	**2048**	**10665**	**6**	
Total predicted / Total true	**1.11**	**0.85**	**0.91**	**0.79**	**0.86**	**0.70**	**1.16**	**0.03**	

New Zealand Parliamentary Speeches

- All parliament speeches, 1987-2002.
  - $437\mathrm{K}$ speeches in total, removed procedural remarks, short speeches, and foreign-language speeches, to get 290K for analysis.
  - speeches linked to speaker and parliamentary debate type.

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  - $437\mathrm{K}$ speeches in total, removed procedural remarks, short speeches, and foreign-language speeches, to get 290K for analysis.
  - speeches linked to speaker and parliamentary debate type.
- Apply featurization pipeline and logistic model to get predicted topic probabilities for each speech.

(a) economy

(b) external relations

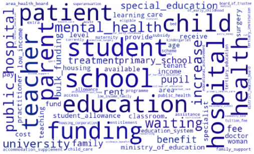
(e) political system

(f) social groups

(c) fabric of society

(d) freedom and democracy

(g) welfare and quality of life



(h) no topic

Validation with Target-Corpus Annotation

Table 3: Human Coding vs. Predicted Manifesto Topics

	Top 1	Top 3	Top 5	N
8 topics				
Welfare and quality of life	62	91	98	796
Political system	57	90	98	1,069
External relations	56	84	91	94
Fabric of society	55	87	97	433
Economy	54	85	95	721
Social groups	37	71	88	325
Freedom and democracy	37	71	88	545
no topic	1	2	12	192
Total	51	82	92	4,175

- We sampled 4,175 NZ speeches and a manifesto coder annotated them.
- In 44-topic spec, overall top-1 accuracy is 41% and top-3 accuracy is 65%

Experiment: Electoral Reform in New Zealand

- A 1993 reform in New Zealand moved from majoritarian to proportional representation:
  - **Majoritarian (first past the post)**: two parties, single party controls parliament.
  - **Proportional representation**: many minority parties, coalition governments.

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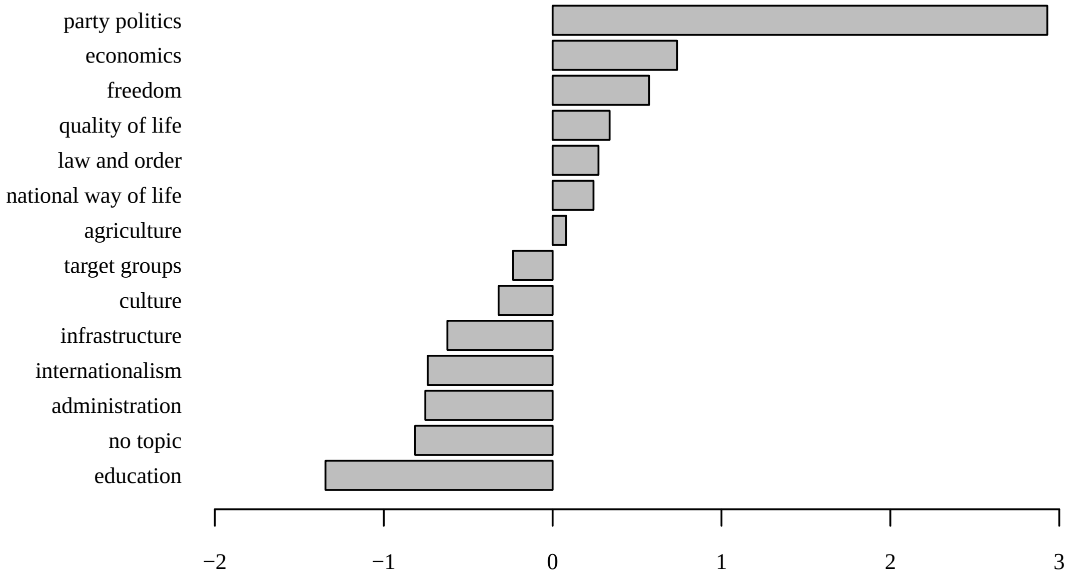
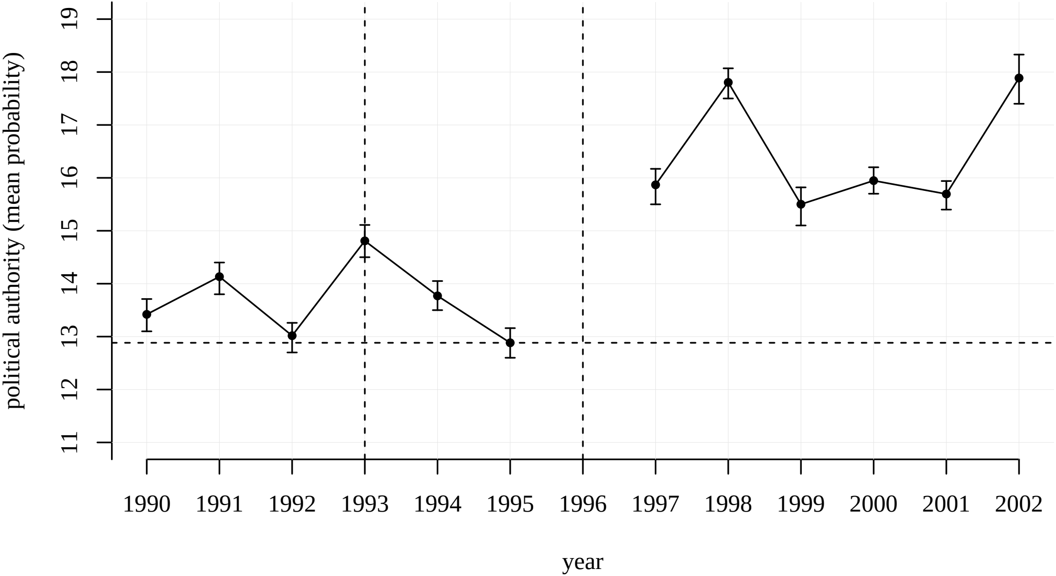
- How did it affect speech topics in the New Zealand Parliament?

Change in Parliament Attention due to Reform



Change in Party Politics Topic



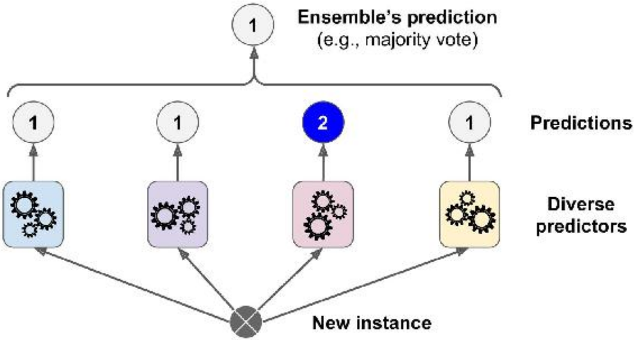
Example "Party Politics" Speech

Osnabruegge, Ash, Morelli (2019)

"I have seen seven Opposition leaders in my time, but I have never seen a leader as relentlessly negative as Helen Clark. . . . How could anybody be so negative, day in, day out? It could get into the Guinness Book of Records. She does not have a positive word to say about anything. It is all negative, negative, negative."

- Parliamentarian Richard Prebble, 15 Feb 1999

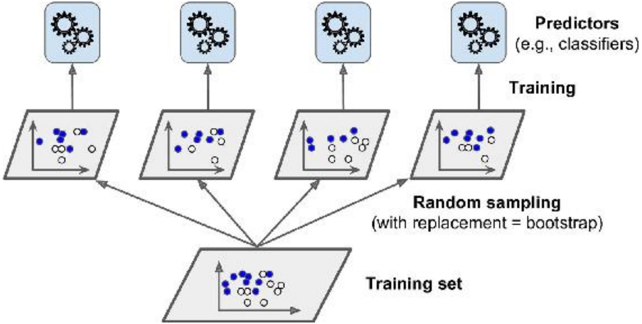
Voting Classifiers



- 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.

Bagging (Bootstrapping)

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



  - This is called **bagging** (bootsrap aggregating, when sampling with replacement) or **pasting** (when sampling without replacement).
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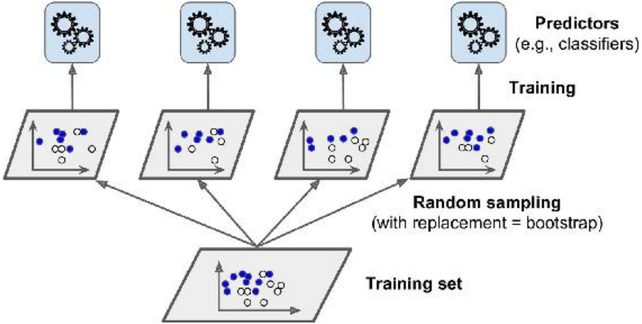
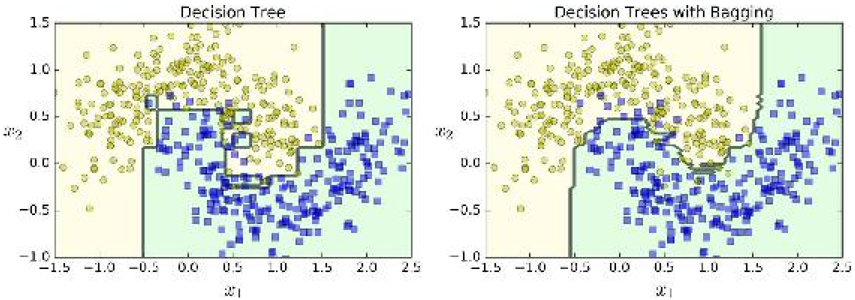


  - This is called **bagging** (bootsrap aggregating, when sampling with replacement) or **pasting** (when sampling without replacement).
  - can also use different subsets of features across subclassifiers.
- The ensemble predicts by aggregating the predictions:
  - for regression, use the mean/median output
  - for classification, can use the mean/median predicted probability or most frequent prediction

Bagging Benefits



- While the individual predictors have a higher bias than a predictor trained on all the data, aggregation reduces both bias and variance.
  - Generally, the ensemble 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.

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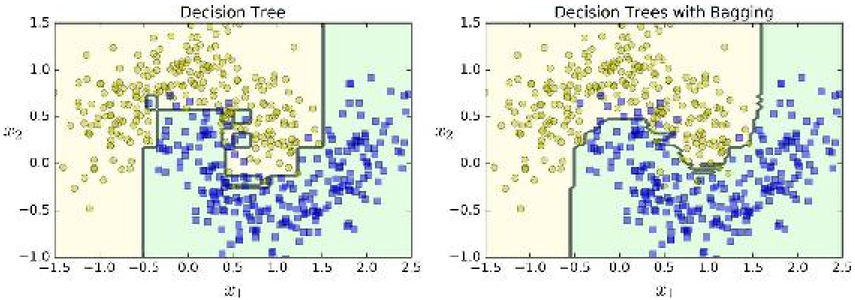

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  - Generally, the ensemble has a similar bias but lower variance than a single predictor trained on all the data.
- Predictors can be trained in parallel using separate CPU cores.
- Also gives you a distribution of predictions, which useful when using predictions for downstream empirical analysis.

Random Forests and Gradient Boosting

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  - optimized voting ensembles of decision trees.
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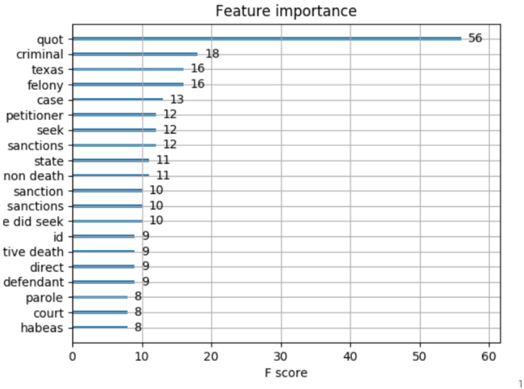
- Gradient boosting machines:
  - works by sequentially adding predictors to an ensemble – fits the new predictor to the residual errors made by the previous predictor to gradually improve the model.
  - give state-of-the-art performance except (sometimes) deep neural nets.

Feature Importance

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

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



- Random forests and boosted trees provide a metric of feature importance that summarizes how well each feature contributes to predictive accuracy.

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6. Answer the research question!