Applications of metric evaluation

PREDICTING CTR WITH MACHINE LEARNING IN PYTHON

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Four categories of outcomes

	Actual Positives	Actual Negatives
Positive Predictions	True Positives (TP)	False Positives (FP)
Negative Predictions	False Negatives (FN)	True Negatives (TN)

- First part of category (true/false) represents whether model was correct or not
- Second part of the category (positive/negative) represents the target label the model applied

Interpretations of four categories

- If model predicts there is a click, then there is a bid for that impression which costs money
- If no click predicted, no bidding and hence no cost
- True positives (TP): money gained (impressions paid for that were clicked on).
- False positives (FP): money lost (impressions that were paid for, but not clicked).
- True negatives (TN): money saved (no click predicted so no impressions bought).
- False negatives (FN): money lost out on (no click predicted, but would have been actual click in reality).

Confusion matrix

```
print(confusion_matrix(y_test, y_pred))
```

```
[[8163  166]
 [1517  154]]
```

```
# Order: tn, fp, fn, tp
print(confusion_matrix(y_test, y_pred).ravel())
```

```
[8163, 166, 1517, 154]
```

ROI analysis

- Assume: some cost `c` and return `r` per X number of impressions

```
total_return = tp * r
```

```
total_cost = (tp + fp) * c
```

```
tp * r > (tp + fp) * c
```

```
roi = total_return / total_spent
```

Let's practice!

Model evaluation

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Precision and recall

- Precision: proportion of clicks relative to total number of impressions, `TP / (TP + FP)`
  - Higher precision means higher ROI on ad spend
- Recall: the proportion of clicks gotten of all clicks available, `TP / (TP + FN)`
  - Higher recall means better targeting of relevant audience

Calculating precision and recall

```
print(precision_score(
  y_test, y_pred, average = 'weighted'))
```

```
0.73
```

```
print(recall_score(
  y_test, y_pred, average = 'weighted'))
```

```
0.75
```

Baseline classifiers

- It is important to evaluate classifiers relative to an appropriate baseline
  - The baseline here, due to imbalanced nature of click data, is a classifier that always predicts no click

```
y_pred = np.asarray([0 for x in range(len(X_test))])
```

```
[[0]
 [0] ...]
```

Implications on ROI analysis

- For the baseline classifier, `tp` and `fp` will be zero
- Therefore total return and total spend will be zero, and ROI undefined
- Confusion matrix via `confusion_matrix()` along with `ravel()` to get the four categories of outcomes

```
total_return = tp * r
total_spent = (tp + fp) * cost
roi = total_return / total_spent
```

Let's practice!

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Tuning models

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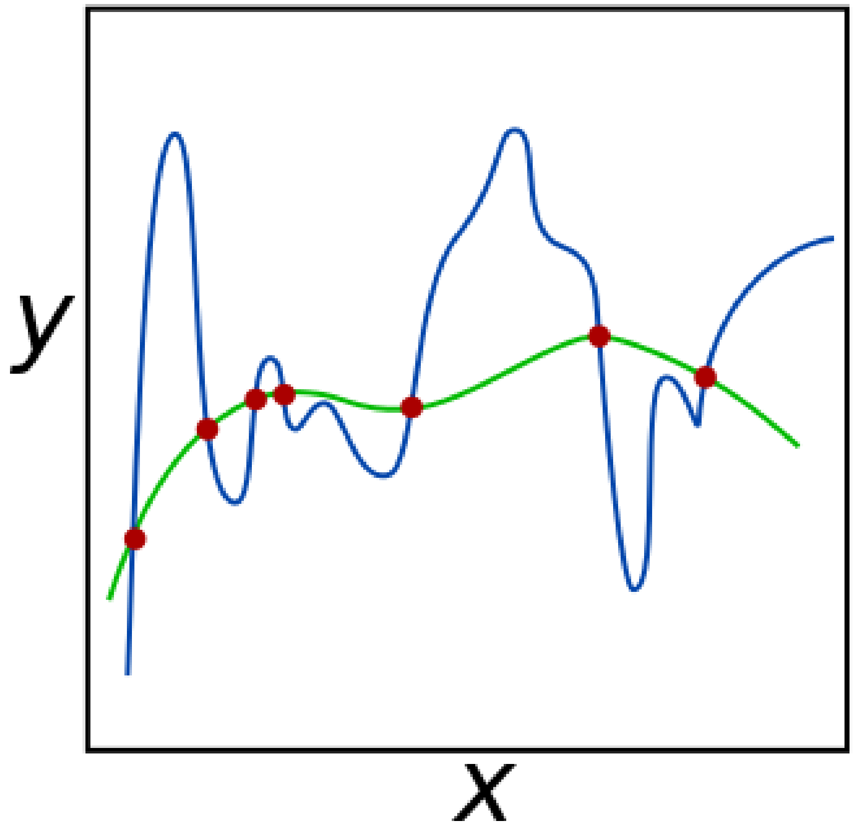
Regularization

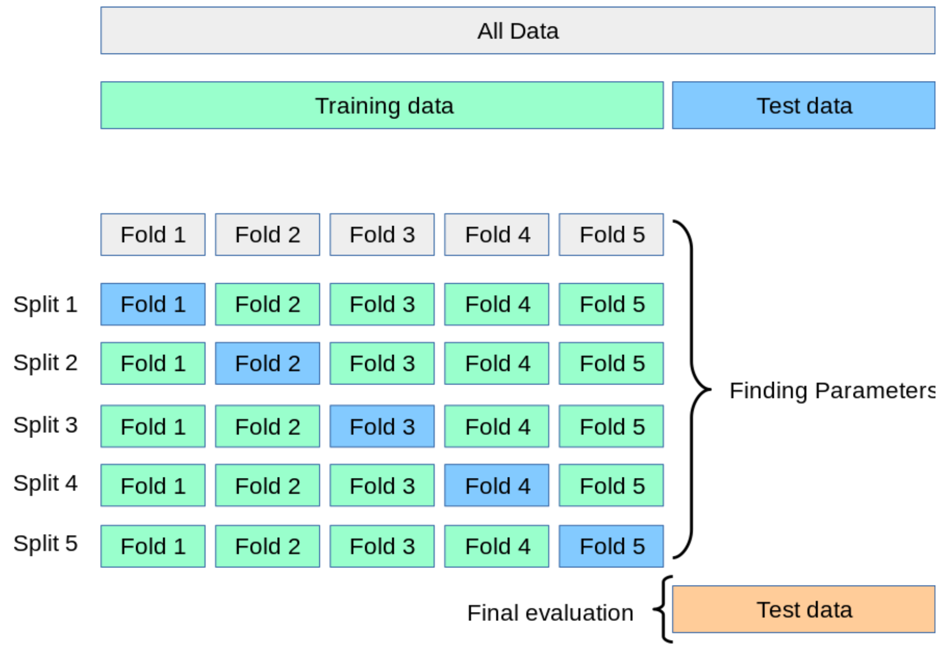


- Regularization: addressing overfitting by altering the magnitude of coefficients of parameters within a model
- Regularization can increase performance metrics and hence ROI on ad spend

Examples of regularization

- Logistic Regression: the `C` parameter is the inverse of the regularization strength.
- From least to most complex: `C=0.05 < C=0.5 < C=1`
- Decision Tree: the `max_depth` parameter controls how many layers deep the tree can grow.
- From least to most complex: `max_depth=3 < max_depth=5 < max_depth=10`

Cross validation



- For each of the `k` folds, that fold will be used as a testing set (for validation) while other `k-1` are used as training.
- Therefore, you have `k` evaluations of model performance.
- Note you still have the separate evaluation testing set.

Examples of cross validation

```
k_fold = KFold(n_splits = 4, random_state = 0)
```

```
for i in [3, 5, 10]:
  clf = DecisionTreeClassifier(max_depth = i)
  cv_precision = cross_val_score(
    clf, X_train, y_train, cv = k_fold,
    scoring = 'precision_weighted')
```

- Scoring strings: `precision_weighted, recall_weighted, roc_auc`

Let's practice!

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Ensembles and hyperparameter tuning

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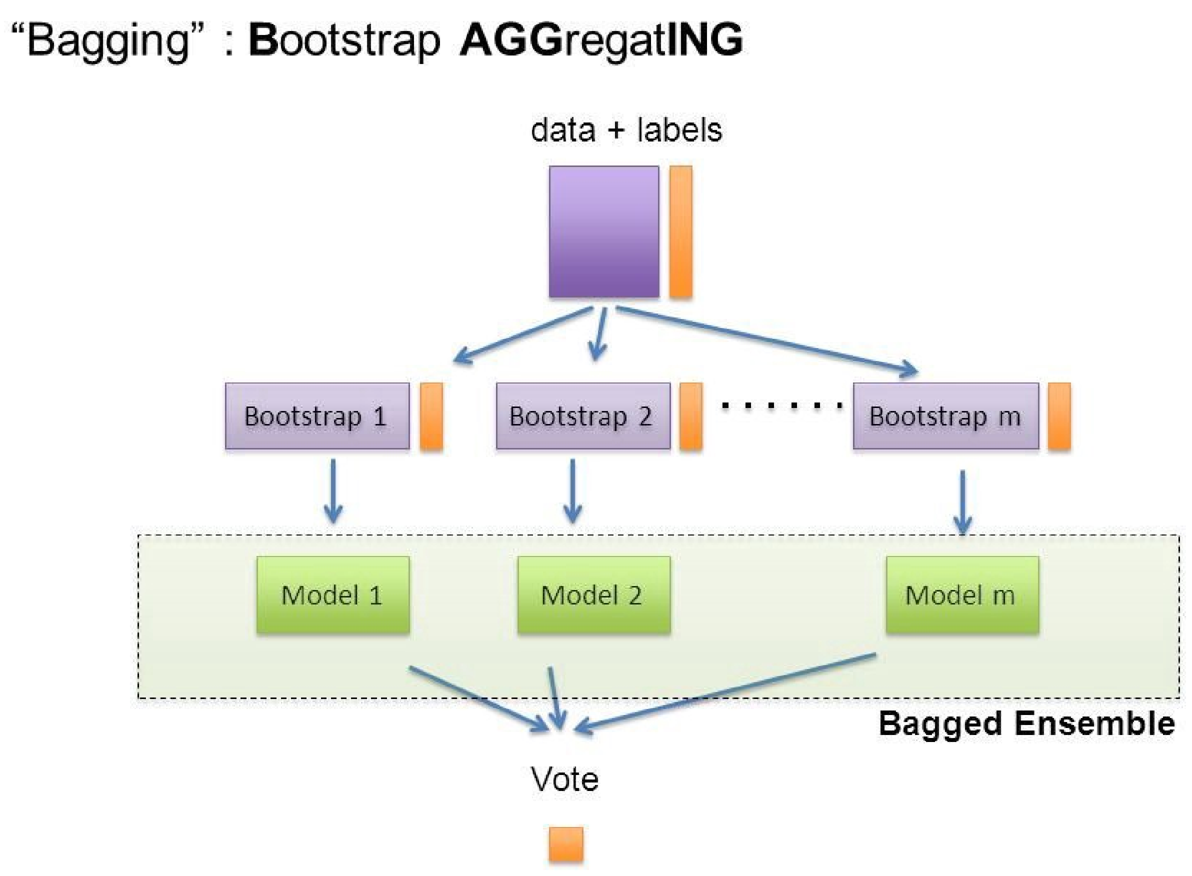
Ensemble methods



- Bagging: random samples selected for different models, then models are individually trained and combined.

Random forests

```
clf = RandomForestClassifier()
print(clf)
```

```
RandomForestClassifier(
  bootstrap=True,
  ...
  max_depth = 10,
  ...
  n_estimators = 100,
  ...)
```

Hyperparameter tuning

- Hyperparameter: parameters configured before training, and external to a model
- Examples of parameters but NOT hyperparameters: slope coefficient in linear regression, weights in logistic regression, etc.
- Examples of hyperparameters: `max_depth` , `n_estimators` , etc.

Grid search

```
param_grid = {'n_estimators': n_estimators,
              'max_depth': max_depth}
```

```
clf = GridSearchCV(estimator = model,
                   param_grid = param_grid,
                   scoring = 'roc_auc')
print(clf.best_score_)
print(clf.best_estimator_)
```

```
0.6777
RandomForestClassifier(max_depth = 100, ...)
```

Let's practice!

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