TAMPERE UNIVERSITY OF TECHNOLOGY

# SIGNAL INTERPRETATION

## Lecture 7: Error Assessment and Regularization

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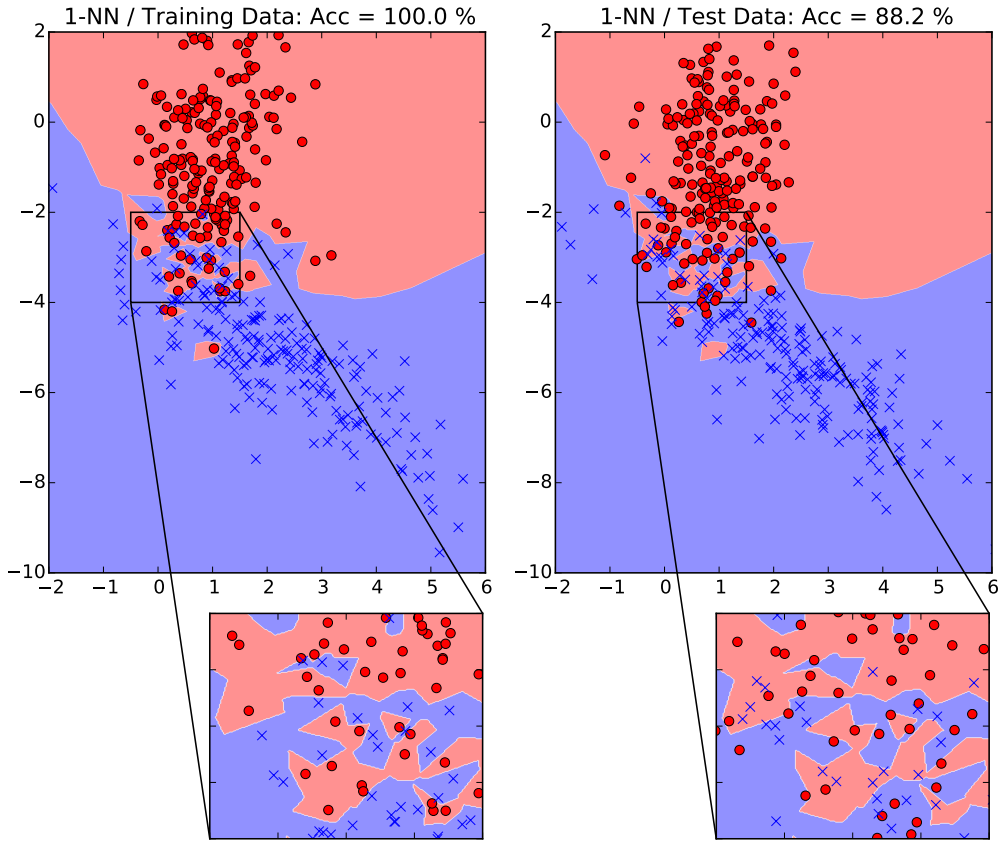
# ERROR ASSESSMENT AND OVERFITTING

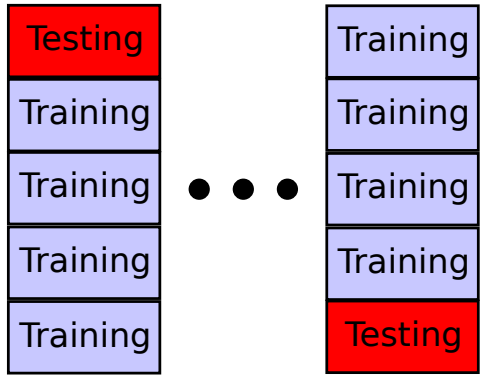
# Generalization

- The important thing is how well the classifier works with unseen data.
- An overfitted classifier memorizes the training data and does not generalize.



# Cross-validation

- The generalization ability of a classifier needs to be tested with **unseen** samples.
- In practice this can be done by splitting the data into separate training and test sets.
- A standard approach is to use *K*-fold cross-validation:
  - Split the training data to *K* parts (called folds)
  - Use each fold for testing exactly once and train with the other folds
  - The error estimate is the mean of the *K* estimates
- A common value for *K* is 5 or 10.



# Cross-validation in sklearn

- Cross-validation is extremely elegant in sklearn.
- Essentially 1 line of code is required:

```
from sklearn.cross_validation \
     import cross_val_score
scores = cross_val_score(clf, X, y)
```

- The cross-validator receives the classifier and the data and returns a list of scores for each test fold.
- The function can receive additional parameters that modify the number of folds, possible stratification (balancing the classes in folds), etc.

Code:

```
77 # Cross-validate to estimate accuracy
78
79 scores = cross_val_score(clf,
80                          X,
81                          y,
82                          cv = 10,
83                          n_jobs = 2)
84
85 for fold in range(10):
86     print "Fold %d score: %.2f %%" % \
87           (fold, 100*scores[fold])
88
89 print "-" * 10
90 print "CV accuracy: %.2f %%" % \
91       (100*np.mean(scores))
```

Result:

```
Fold 0 score: 95.65 %
Fold 1 score: 100.00 %
Fold 2 score: 100.00 %
Fold 3 score: 100.00 %
Fold 4 score: 86.36 %
Fold 5 score: 100.00 %
Fold 6 score: 100.00 %
Fold 7 score: 100.00 %
Fold 8 score: 100.00 %
Fold 9 score: 90.48 %
----------
CV accuracy: 97.25 %
```

# Stratified Cross-validation

- The CV split can be controlled using the cv argument.
- Instead of a completely random split, a **stratified** split is preferred: Each fold will hold a mixture of classes in same proportion as in full dataset.
- The stratified split can be generated easily:

```
>>> from sklearn.cross_validation import StratifiedKFold
# Generate SKF split. This needs the class labels y.
>>> skf = StratifiedKFold(y, 10)

# skf is a generator; we can transform it into a list.
>>> print list(skf)[0]
(array([0, 1, 4, ... , 399]), array([2, 3, 10, ... , 390]))
# Contains 10 train-test index pairs, above the first one.
# Each index set has same proportion of samples from each
      class.
```

```
# CV score estimation
from sklearn.cross_validation import
     cross_val_score, StratifiedKFold

skf = StratifiedKFold(y, 10, shuffle =
       True)
scores = cross_val_score(clf, X, y,
                         cv = skf)
```

```
# Print scores

>>> print ("Accuracy: %.2f +- %.2f" %
          (np.mean(scores),
           np.std(scores)))

Accuracy: 0.91 +- 0.04
```

# Leave-One-Out CV

- A popular accuracy estimation strategy is to use **Leave-One-Out** (LOO) split.
- Extreme case of *K* fold CV with *K* equal to number of samples.
- Requires lot of computation: If there are *N* samples in training set, we need to train *N* times.
- Also: surprisingly large variance.

```
# CV score estimation
from sklearn.cross_validation import
       LeaveOneOut

loo = LeaveOneOut(y.size)
scores = cross_val_score(clf, X, y,
                         cv = loo)
```

```
# Print scores

>>> print ("Accuracy: %.2f +- %.2f" %
           (np.mean(scores),
            np.std(scores)))

Accuracy: 0.92 +- 0.28
```

# Leave-One-Label-Out CV

- Sometimes the data is recorded from multiple sources, and we wish to test the generalization over sources.
- For example: Data is recorded in 10 sessions; we wish to train with 9 and test with one.
- Or: we get images from 10 cameras and would like to have a model that is robust when the 11th camera is added.
- Applies to the course competition, as well.

```
# CV score estimation
from sklearn.cross_validation import
       LeaveOneLabelOut

# Suppose these are these (e.g.,
       camera indices per sample).
labels = [1,1,1,2,2,2,3,3,3,3,4,4]
lolo = LeaveOneLabelOut(labels)
scores = cross_val_score(clf, X, y,
                         cv = lolo)
```

# Other Error Metrics

- Error estimation is not limited to accuracy.
- Any error metric can be used instead.
- Popular ones are invoked easily, but you can also implement your own.
  - `'accuracy'`: Accuracy score (default)
  - `'roc_auc'`: Area under ROC curve
  - `'recall'`: How many % of positive samples were found
  - `'precision'`: How many % of found samples were positive
  - `'f1'`: $F_1$ score; harmonic mean of recall and precision

```
# Code:

metrics = ['accuracy',
           'roc_auc',
           'recall',
           'precision',
           'f1']

for scorer in metrics:
    scores = cross_val_score(clf,
                     X,
                     y,
                     scoring = scorer)

print ("%s score: %.2f +- %.2f" % \
      (scorer,
       np.mean(scores),
       np.std(scores)))
```

```
# Result:

accuracy score: 0.92 +- 0.01
roc_auc score: 0.98 +- 0.00
recall score: 0.90 +- 0.03
precision score: 0.93 +- 0.01
f1 score: 0.91 +- 0.02
```

# Cross-validating a set of Classifiers

- A nice property of sklearn is that each predictor conforms to the same interface (*i.e.*, each implements `.fit()`, and `.predict()` methods).
- Thus, we can examine a list of them in a `for` loop easily.

Code:

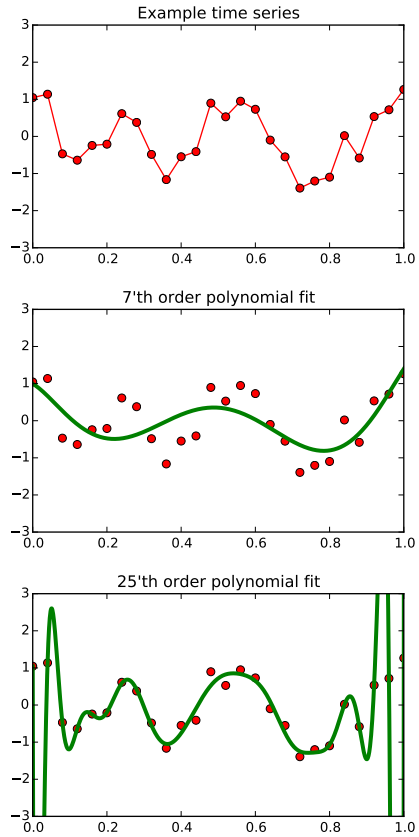
```
100 # Test a collection of classifiers
101
102 classifiers = [LogisticRegression(),
103                LDA(),
104                LinearSVC(),
105                SVC(),
106                RandomForestClassifier(),
107                KNeighborsClassifier()
108                ]
109
110 names = ['LogReg',
111          'LDA',
112          'LinSVM',
113          'SVM',
114          'RF',
115          'NN']
116
117 for i, clf in enumerate(classifiers):
118
119     scores = cross_val_score(clf,
120                              X,
121                              y,
122                              cv = 10,
123                              n_jobs = 2)
124     print "Classifier %s: score = %.2f %%" % \
125           (names[i], 100*np.mean(scores))
```

Result:

```
Classifier LogReg: score = 97.25 %
Classifier LDA: score = 94.39 %
Classifier LinSVM: score = 97.25 %
Classifier SVM: score = 79.82 %
Classifier RF: score = 89.35 %
Classifier NN: score = 88.50 %
```

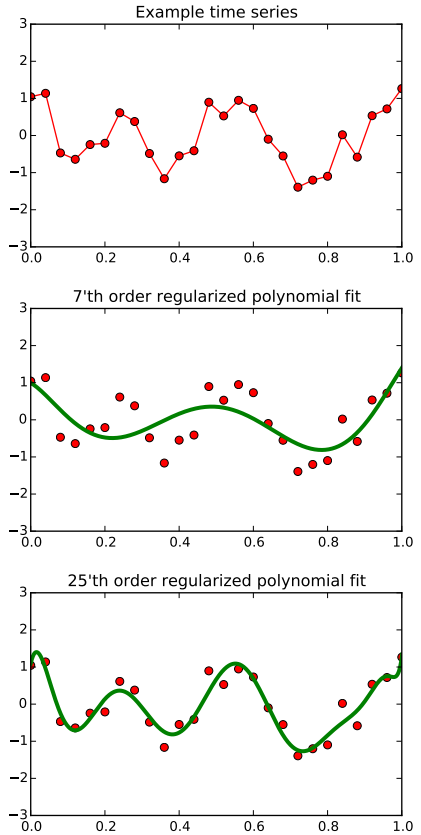
# Overfitting

- Generalization is also related to *overfitting*.
- On the right, a polynomial model is fitted to a time series to minimize the error between the samples (red) and the model (green).
- As the order of the polynomial increases, the model starts to follow the data very faithfully.
- Low-order models do not have enough expression power.
- High-order models are over-fitting to noise and become "unstable" with crazy values near the boundaries.



# Regularization

- Regularization adds a penalty term to the fitting error.
- The model is encouraged to use small coefficients.
- Large coefficients are expensive, so the model can afford to fit only to the major trends.
- On the right, the high order model has a good expression power, but does still not follow the noise patterns.



# Regularization in Regression

- Regularization techniques were first assessed in a regression context with linear models.
- Linear regression model assumes that the inputs $\mathbf{x}_n \in \mathbb{R}^P$ and outputs $\mathbf{y}_n \in \mathbb{R}$ are related as

$$y_n = \mathbf{w}^T \mathbf{x}_n + e_n,$$

  where $\mathbf{e}_n \sim \mathcal{N}(0, \sigma^2)$ is the error term.
- With these assumptions, *least squares* returns the optimal solution:

$$\underset{\mathbf{w}}{\text{minimize}} \left( \sum_{n=0}^{N-1} (y_n - \mathbf{w}^T \mathbf{x}_n)^2 \right)$$

- There exists a closed form solution for LS:

$$\mathbf{w}_{\text{LS}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}.$$

  with $\mathbf{X} = \left[ \mathbf{x}_0^T, \mathbf{x}_1^T, \ldots, \mathbf{x}_{N-1}^T \right]^T$.

# Regularization in Regression

- The most straightforward regularization technique adds a squared penalty with weight $\lambda > 0$ for the weights:

$$\underset{\mathbf{w}}{\text{minimize}} \left( \sum_{n=0}^{N-1} (y_n - \mathbf{w}^T \mathbf{x}_n)^2 + \lambda \mathbf{w}^T \mathbf{w} \right).$$

- This is called *Tikhonov regularization* or *Ridge Regression*, and there is a closed form solution:

$$\mathbf{w}_{\text{RIDGE}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^T \mathbf{y}.$$

- Another name is $L_2$ regularization, because we take the $L_2$ norm of the weights.
- In general, the $L_q$ norm (for $q > 0$) is defined as

$$\|\mathbf{w}\|_q = \left( |w_0|^q + |w_1|^q + \cdots + |w_{P-1}|^q \right)^{-q}$$

- See `sklearn.linear_model.Ridge`.

# L1 Regularization in Regression

- More recently, $L_1$ penalty has become popular—simply change the squared penalty into absolute penalty:

$$\underset{\mathbf{w}}{\text{minimize}} \left( \sum_{n=0}^{N-1} (y_n - \mathbf{w}^T \mathbf{x}_n)^2 + \lambda \|\mathbf{w}\|_1 \right),$$

  with $\lambda \|\mathbf{w}\|_1 = \sum_p |w_p|$.
- This is called *LASSO penalty*[1].
- With this penalty, there is no closed form expression.
- The minimum is solved iteratively using, *e.g.*, gradient search.
- See `sklearn.linear_model.Lasso`.

[1] (Least Absolute Shrinkage and Selection Operator)

# $L_2$ Regularization with Linear Classifiers

- The same regularizers apply also for linear classifiers.
- $L_2$ **penalized Logistic Regression**:

$$\text{penalized log-loss} = \sum_{n=0}^{N-1} \underbrace{\ln(1+\exp(y_n \mathbf{w}^T \mathbf{x}_n))}_{\text{log-loss}} + \lambda \underbrace{\mathbf{w}^T \mathbf{w}}_{\text{penalty}}$$

- $L_2$ **penalized Linear SVM**:

$$\text{penalized hinge loss} = \sum_{n=0}^{N-1} \underbrace{\max(0, 1 - y_n \mathbf{w}^T \mathbf{x}_n)}_{\text{hinge loss}} + \lambda \underbrace{\mathbf{w}^T \mathbf{w}}_{\text{penalty}}$$

- The coefficient $\lambda \geq 0$ balances the strength of regularization:
  - Large $\lambda$: small coefficients (heavy penalty for large $\mathbf{w}^T \mathbf{w}$)
  - Small $\lambda$: large coefficients (small penalty for large $\mathbf{w}^T \mathbf{w}$)

# $L_1$ Regularization with Linear Classifiers

- More recently, research has concentrated around the $L_1$ norm: $\|\mathbf{w}\|_1 = \sum |w_k|$.
- $L_1$ **Regularized Logistic Regression**:

$$\text{penalized log-loss} = C \sum_{n=0}^{N-1} \underbrace{\ln(1 + \exp(y_n \mathbf{w}^T \mathbf{x}_n))}_{\text{log-loss}} + \underbrace{\|\mathbf{w}\|_1}_{L_1 \text{ penalty}}$$

- $L_1$ **Regularized Linear SVM**:

$$\text{penalized log-loss} = C \sum_{n=0}^{N-1} \underbrace{\max(0, 1 - y_n \mathbf{w}^T \mathbf{x}_n)}_{\text{hinge loss}} + \underbrace{\|\mathbf{w}\|_1}_{L_1 \text{ penalty}}$$

# Sparsity

- A key benefit of $L_1$ is that it promotes *sparse* weight vectors; *i.e.,* most entries of $\mathbf{w}$ are zero.
- This is equivalent to **feature selection:** most features are multiplied by zero, thus discarding them completely.
- Feature selection property can be understood from an alternative formulation of the optimization problem.
- The following two problems are equivalent

$$\text{minimize} \sum_{n=0}^{N-1} \ell(\mathbf{w}) + \lambda \|\mathbf{w}\|_p$$

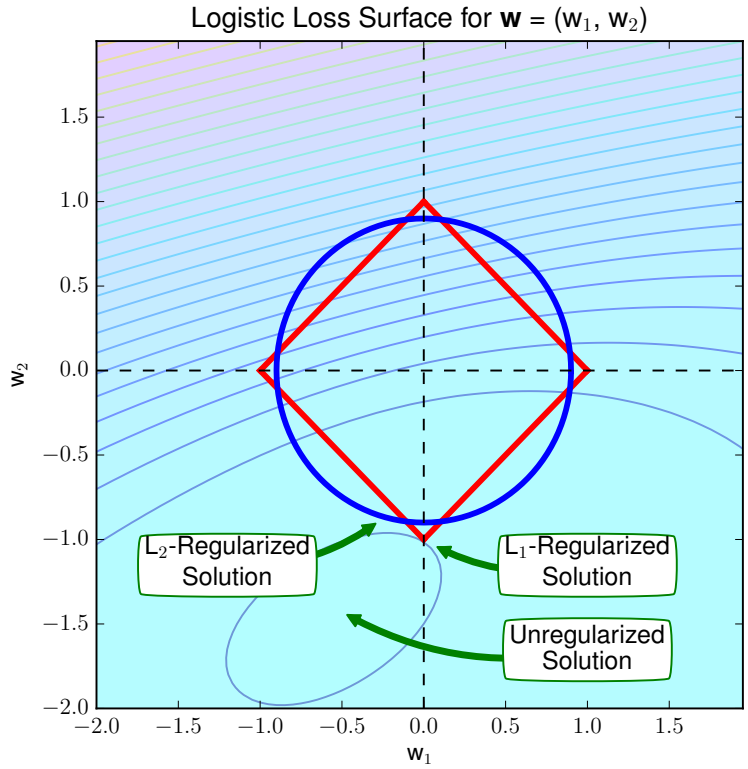
and

$$\text{minimize} \sum_{n=0}^{N-1} \ell(\mathbf{w}) \text{ such that } \|\mathbf{w}\|_p \leq C$$

with $\ell(\mathbf{w})$ either the log loss or hinge loss and $p \in \{1, 2\}$.

# Sparsity

- The parameters $\lambda$ and $C$ are obviously different.
- However, there is a one-to-one mapping: for each $\lambda$ we can find the corresponding $C$ that gives the same solution.
- In the latter formulation, we try to find the weight vector that minimizes the loss inside the region $\|\mathbf{w}\|_p \leq C$.
- This region is circular for $L_2$ and diamond shaped for $L_1$.
- With $L_1$, the solutions are often at the corners of the diamond.

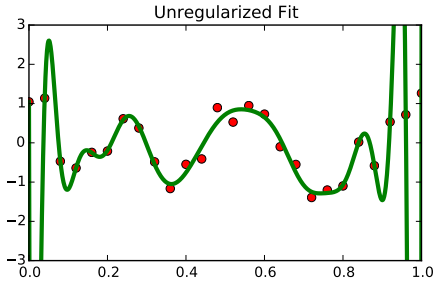


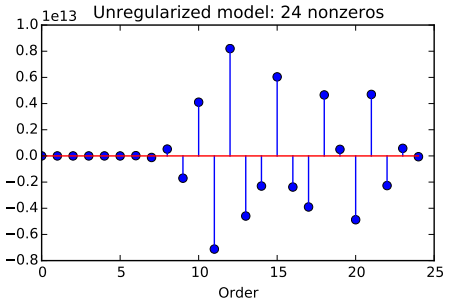

*The $L_1$ solution tends to lie along the coordinate axes, where some of the coefficients are zero.*

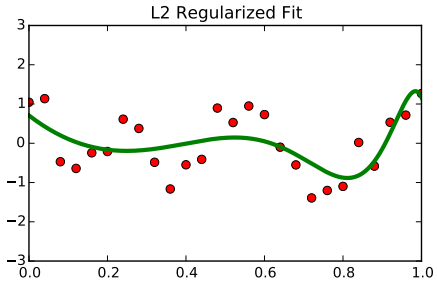
*This is more likely if the area size decreases (or $C \to 0$).*

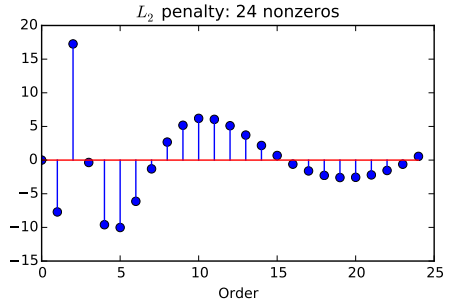
# Sparsity

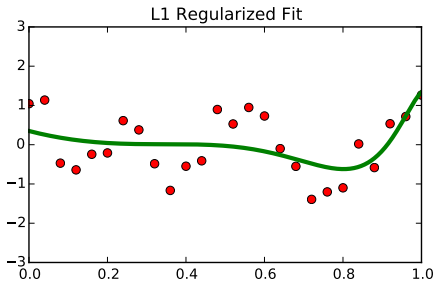
- The plots illustrate the model coefficients without regularization, with traditional regularization and sparse regularization.
- The importance of sparsity is twofold: The model can be used for feature selection, but often also generalizes better.

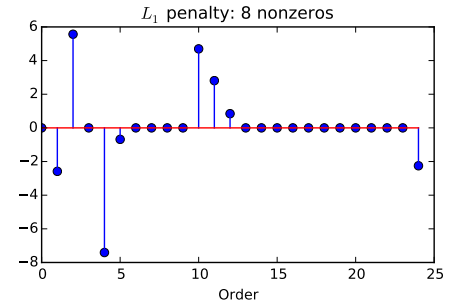


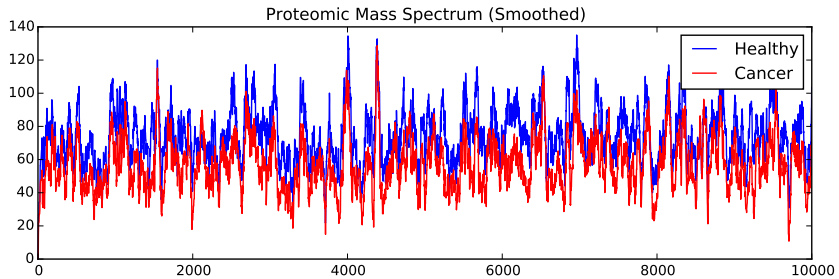



# Regularization in Ovarian Cancer Detection

- We will study an example of classifying proteomic fingerprints of mass-spectra measured from ovarian cancer patients and healthy controls.[2]
- 121 cancer patients and 95 healthy controls.
- Raw mass spectra consists of 10000 measurements.



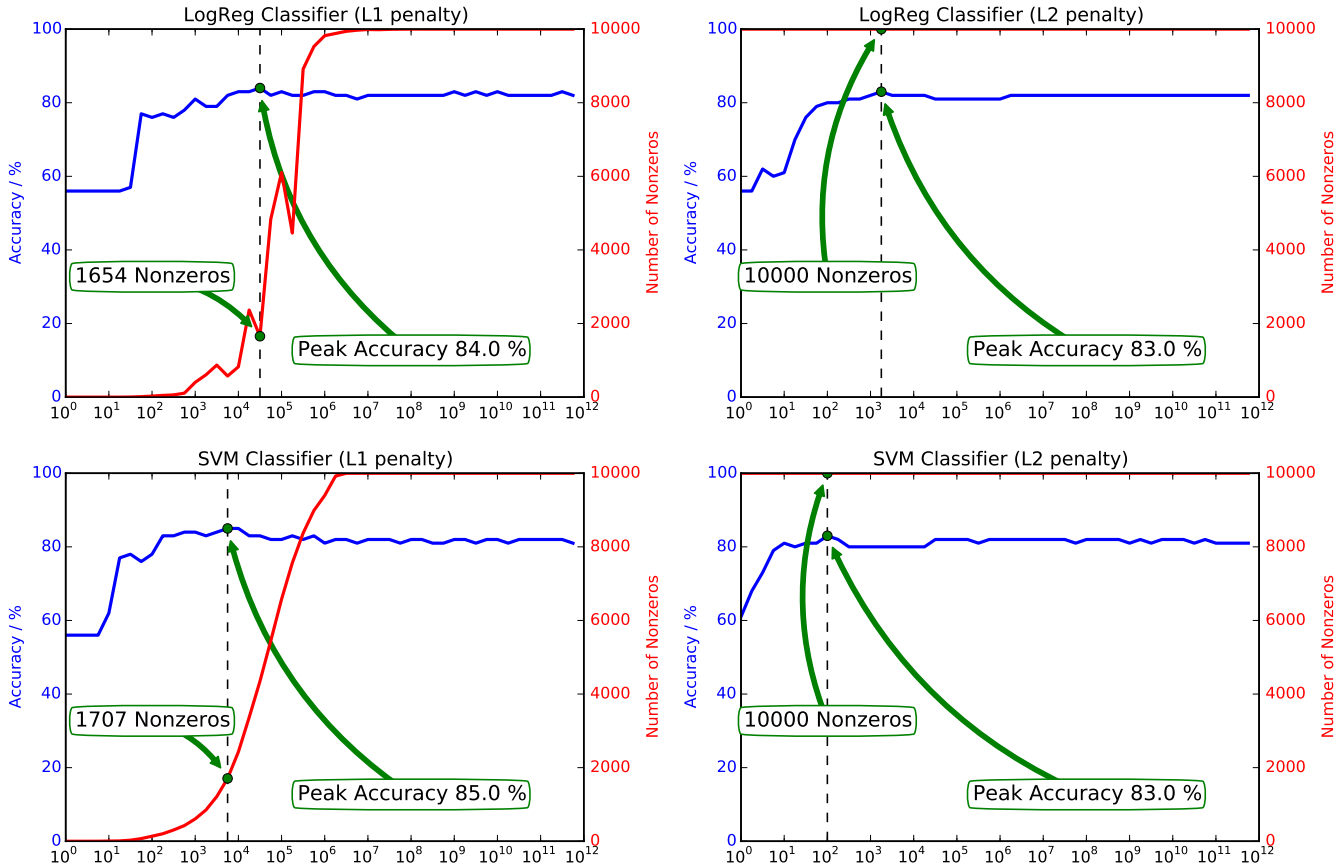

[2] Conrads, Thomas P., et al. "High-resolution serum proteomic features for ovarian cancer detection." *Endocrine-Related Cancer* (2004).

# Training a Classifier

```
classifiers = [(LogisticRegression(), "LogReg"),
               (LinearSVC(dual = False), "SVM")]
C_range = 10.0 ** np.arange(0,12, 0.25)

for clf, name in classifiers:

    for penalty in ["l1", "l2"]:
        clf.penalty = penalty

        accuracies = []
        nonzeros = []

        for C in C_range:

            clf.C = C
            clf.fit(X_train, y_train)
            prediction = clf.predict(X_test)
            accuracy = 100.0 * np.mean(prediction == y_test)
```

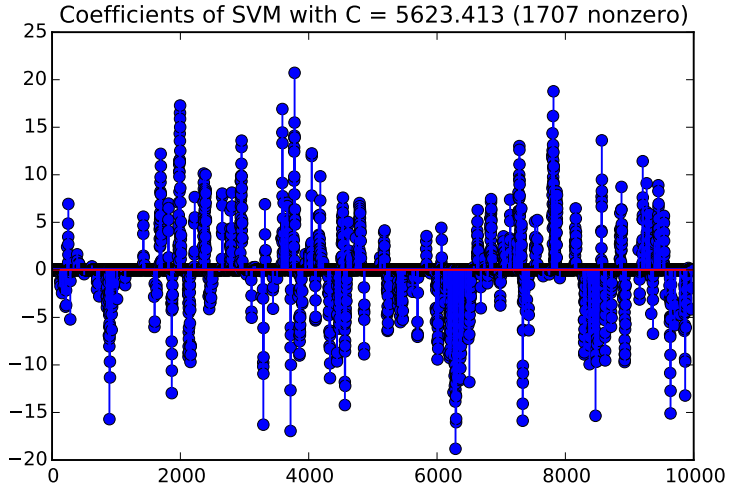
- The attached code trains and applies a LR and SVM classifiers for the ovarian cancer problem.
- We loop over two penalties and a range of regularization parameters *C*.

# Results


LogReg Classifier (L1 penalty)
Accuracy / %
Number of Nonzeros
1654 Nonzeros
Peak Accuracy 84.0 %
LogReg Classifier (L2 penalty)
10000 Nonzeros
Peak Accuracy 83.0 %
SVM Classifier (L1 penalty)
1707 Nonzeros
Peak Accuracy 85.0 %
SVM Classifier (L2 penalty)
10000 Nonzeros
Peak Accuracy 83.0 %

# Analysis of the Classifier

- The $\ell_1$ regularized Linear SVM was the most accurate classifier.
- It is defined by its coefficients **w**.
- The nonzero coefficients correspond to the peaks of the mass spectra.



# Feature Selection

- One of the benefits of $L_1$ regularization is its ability for *feature selection*.
- More specifically, $L_1$ can choose the most essential set of good features and discard the rest.
- Helps in high-dimensional cases.
- Improves performance by removing "confusers"; *i.e.,* measurements which have no predictive value (or may even degrade performance).

# Traditional Approaches to Feature Selection

- **Variance based selection**: Retain features with high variance.
  - Simple to implement; poor performance as variance may not be related to feature importance.
  - `sklearn.feature_selection.VarianceThreshold`
- **Statistics based selection**: Apply statistical tests for dependence between features and labels, *e.g.*, chi-squared test.
  - Good if the assumptions are correct (often not the case).
  - `sklearn.feature_selection.SelectKBest`.
- **Recursive selection**: Progressively add or remove features that seem to improve performance the most.

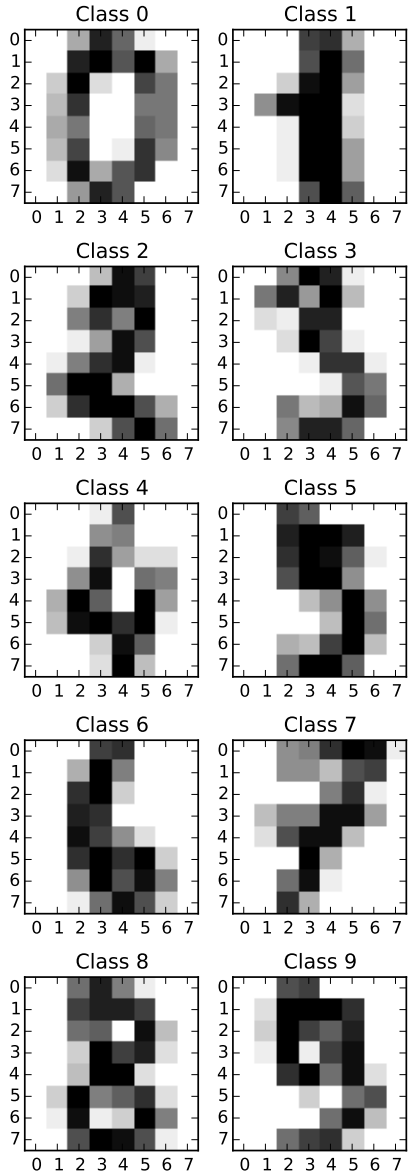
# Traditional Approaches to Feature Selection

- Forward selection starts with empty set and adds variables one by one.
- Backward elimination starts with full set and removes variables one by one.
- There are also hybrid versions that alternate between addition and removal.
- `sklearn.feature_selection.RFECV` implements recursive feature elimination with cross-validated scoring.

# Example

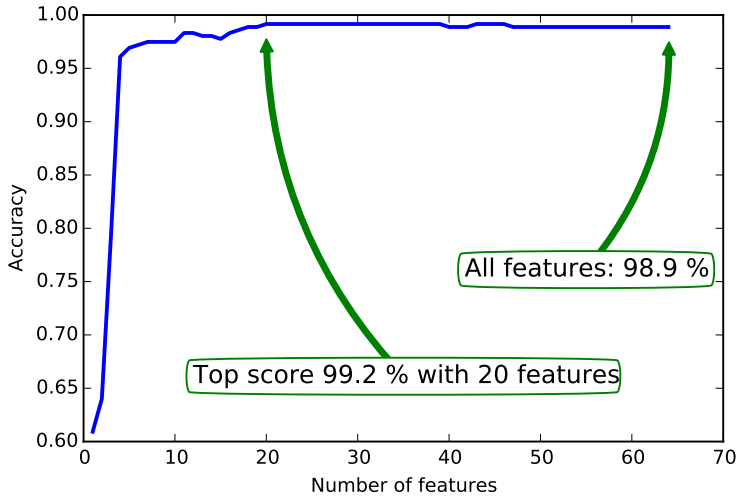
- Consider an example of classifying the *digits* dataset (`sklearn.datasets.load_digits`).
- We use LDA classifier with recursive feature elimination.
- For simplicity, we consider only two classes (zeros and ones).

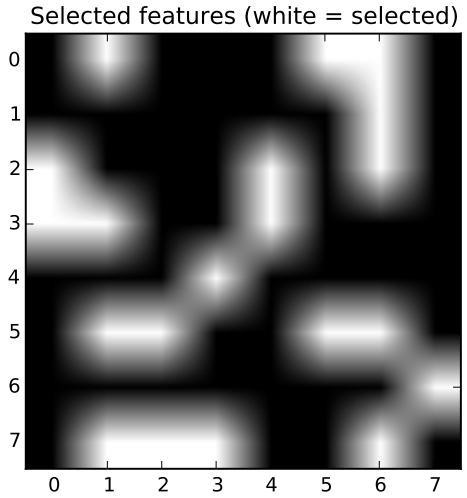
```
from sklearn.datasets import load_digits
from sklearn.lda import LDA
from sklearn.feature_selection import RFECV

digits = load_digits()

# Use only classes 0 and 1
X = digits.data[digits.target < 2, :]
y = digits.target[digits.target < 2]

# Select features
rfecv = RFECV(estimator=LDA())
rfecv.fit(X, y)

# Scores and feature sets are here
scores = rfecv.grid_scores_
mask = rfecv.support_.reshape(8, 8)
```



# Results

- The smallest high scoring set of features consists of 12 pixels.
- There are also larger sets with equal score.
- However, using all features will give a lower score.

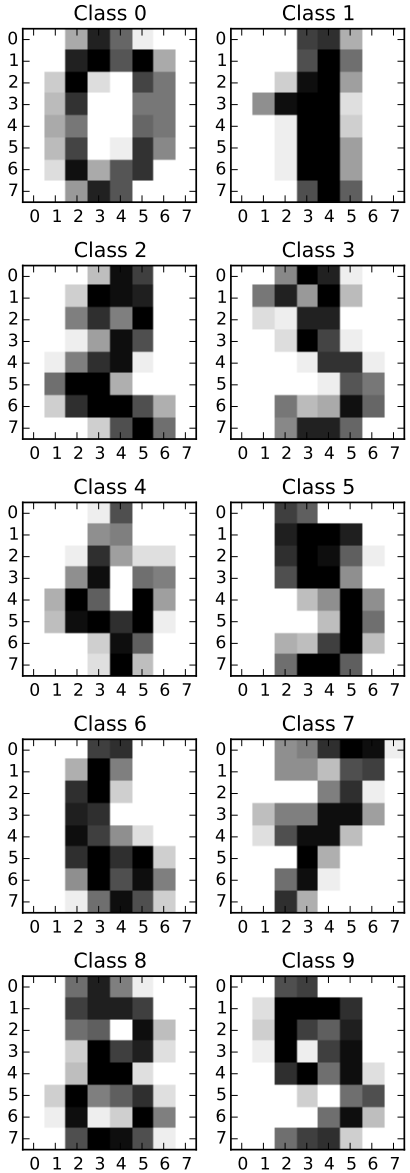


# Example with L1-LR

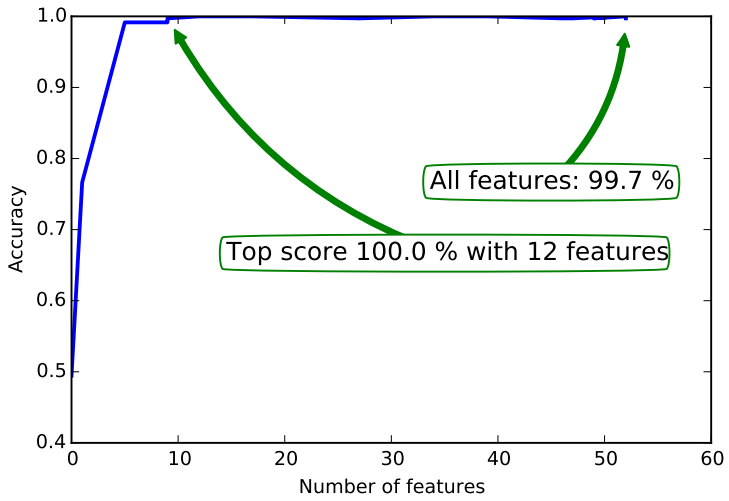
- Let's try to use $L_1$ regularized logistic regression for the same task.

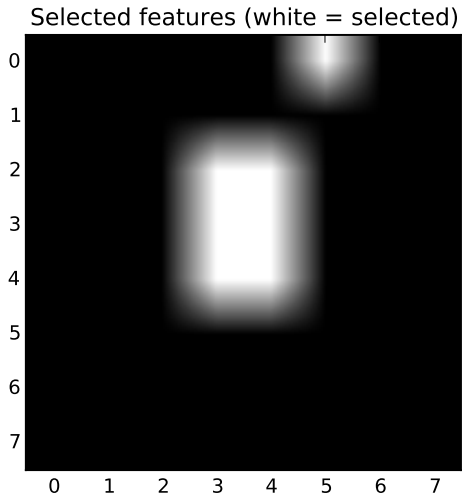
```
from sklearn.datasets import load_digits
from sklearn.linear_model import LogisticRegression
from sklearn.cross_validation import cross_val_score

digits = load_digits()

# Use only classes 0 and 1
X = digits.data[digits.target < 2, :]
y = digits.target[digits.target < 2]

# Select features
clf = LogisticRegression(penalty = "l1")
C_range = 10.0 ** np.arange(-5,6, 0.5)

accuracies = []
nonzeros = []
bestScore = 0

for C in C_range:
    clf.C = C
    score = cross_val_score(clf, X, y, cv = 5).mean()
```



# Example

- The smallest high scoring set of features consists of 27 pixels.
- There are also larger sets with equal score.
- However, using all features will give a lower score.
- The $L_1$ approach seems to be better than RFE.



# Randomized LogReg for Feature Selection

- Basic $L_1$ feature selection has been extended through randomization.
- The randomized version iterates by showing subsamples of the training set and observes which features get selected consistently.
- More robust than normal $L_1$; also called *stability selection*.
- See `sklearn.linear_model.RandomizedLogisticRegression` for classification.
- See `sklearn.linear_model.RandomizedLasso` for regression.

# APPLICATION EXAMPLES

# Applications

- **Application example 1:** ICANN MEG Mind Reading Challenge, June 2011
- **Application example 2:** IEEE MLSP 2012 Birds competition, Sept. 2013
- **Application example 3:** DecMeg2014: Decoding the Human Brain, July 2014

# ICANN MEG Mind Reading Challenge

- We participated in the Mind reading challenge from MEG data organized in the ICANN 2011 conference. [3] [4] [5]

| Rank | Team | Affiliation | Accuracy (%) |
|---|---|---|---|
| 1. | Huttunen et al. | Tampere University of Technology | 68.0 |
| 2. | Santana et al. | Universidad Politecnica de Madrid | 63.2 |
| 3. | Jylänki et al. | Aalto University | 62.8 |
| 4. | Tu & Sun (1) | East China Normal University | 62.2 |
| 5. | Lievonen & Hyötyniemi | Helsinki Institute for Information Technology | 56.5 |
| 6. | Tu & Sun (2) | East China Normal University | 54.2 |
| 7. | Olivetti & Melchiori | University of Trento | 53.9 |
| 8. | Van Gerven & Farquhar | Radboud University Nijmegen | 47.2 |
| 9. | Grozea | Fraunhofer Institute FIRST | 44.3 |
| 10. | Nicolaou | University of Cyprus | 24.2 |

[3] H. Huttunen *et al.*, "Regularized logistic regression for mind reading with parallel validation," *Proc. ICANN/PASCAL2 Challenge: MEG Mind-Reading. Aalto University publication series*, Espoo, June 2011.

[4] H. Huttunen *et al.*, "MEG Mind Reading: Strategies for Feature Selection," in *Proc. of The Federated Computer Science Event 2012*, Helsinki, May 2012.

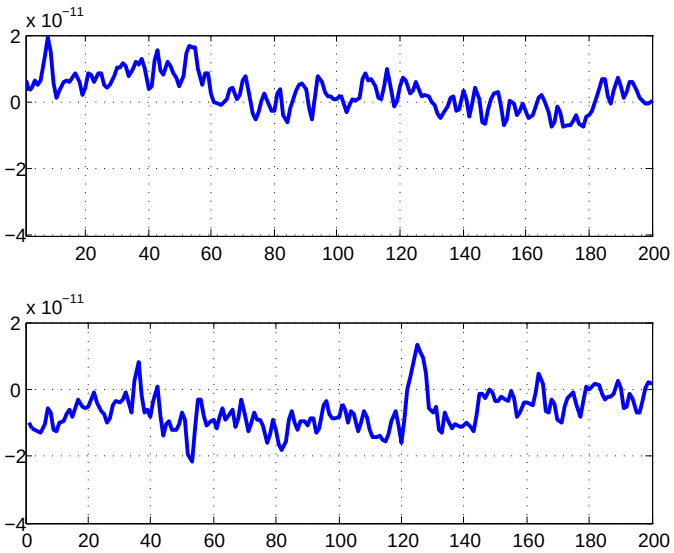
[5] H. Huttunen *et al.*, "Mind Reading with Regularized Multinomial Logistic Regression," *Machine Vision and Applications*, Aug. 2013

# ICANN MEG Mind Reading Challenge Data

- The competition data consists of MEG recordings while watching five different movie categories.
- The data contains measurements of 204 planar gradiometer channels at 200Hz rate, segmented into samples of one second length.
- The task was to design and implement a classifier that takes as an input the MEG signals and produces the predicted class label.
- The training data with annotations had 727 one-second samples, and the secret test data 653 unlabeled samples.
- 50 samples of the training data were special, because they were recorded on the same day as the test data.

# The Curse of Dimensionality

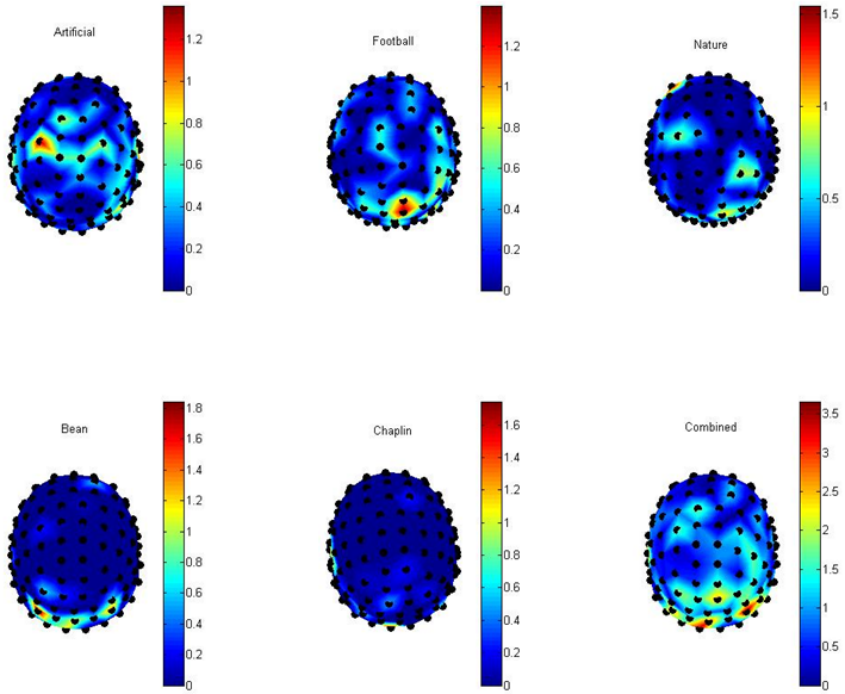
- Since each measurement is a time series, it cannot be fed to classifier directly.
- Instead, we calculated a number of common quantities.
- In all, our pool of features consists of $11 \times 204 = 2244$ features. This means $2244 \times 5 = 11220$ parameters.




| | |
|---|---|
| Intercept | $x_i^{(1)} = \hat{b}_i$ |
| Slope | $x_i^{(2)} = \hat{a}_i$ |
| Variance (d) | $x_i^{(3)} = \frac{1}{N}\sum_{n=1}^{N} \tilde{s}_i^2(n)$ |
| Std. dev. (d) | $x_i^{(4)} = \sqrt{x_i^{(3)}}$ |
| Skewness (d) | $x_i^{(5)} = \frac{1}{N}(x_i^{(4)})^{-3}\sum_{n=1}^{N} \tilde{s}_i^3(n)$ |
| Kurtosis (d) | $x_i^{(6)} = \frac{1}{N}(x_i^{(4)})^{-4}\sum_{n=1}^{N} \tilde{s}_i^4(n)$ |
| Variance | $x_i^{(7)} = \frac{1}{N}\sum_{n=1}^{N}(s_i(n) - \hat{b}_i)^2$ |
| Std. dev. | $x_i^{(8)} = \sqrt{x_i^{(7)}}$ |
| Skewness | $x_i^{(9)} = \frac{1}{N}(x_i^{(8)})^{-3}\sum_{n=1}^{N}(s_i(n) - \hat{b}_i)^3$ |
| Kurtosis | $x_i^{(10)} = \frac{1}{N}(x_i^{(8)})^{-4}\sum_{n=1}^{N}(s_i(n) - \hat{b}_i)^4$ |
| Fluctuation | $x_i^{(11)} = \frac{1}{N-1}\left\lvert\sum_{n=2}^{N}\operatorname{sgn}(s_i(n) - s_i(n-1))\right\rvert$ |

# Where the Selected Features are Located?

- As a side product we gain insight on which areas of the brain were used for prediction.



# IEEE MLSP2013 Birds Competition

- The task of the participants was to train an algorithm to recognize *bird sounds* recorded at the wildlife.
- The recordings consisted of bird sounds from $C = 19$ species, and the sounds were overlapping (with up to 6 birds in a single recording).
- There were altogether 645 ten-second audio clips with sample rate $F_s = 16$ kHz.
- Half of the samples ($N_{\text{train}} = 323$) were used for model training, and half ($N_{\text{test}} = 322$) of the data was provided without annotation.

# IEEE MLSP2013 Birds Competition

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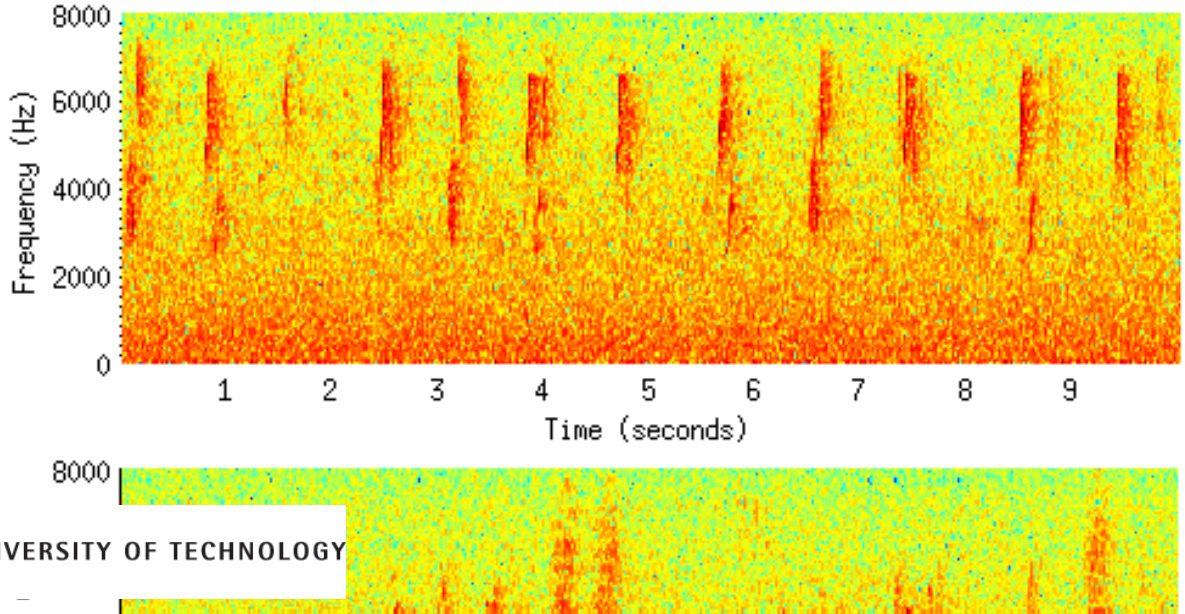
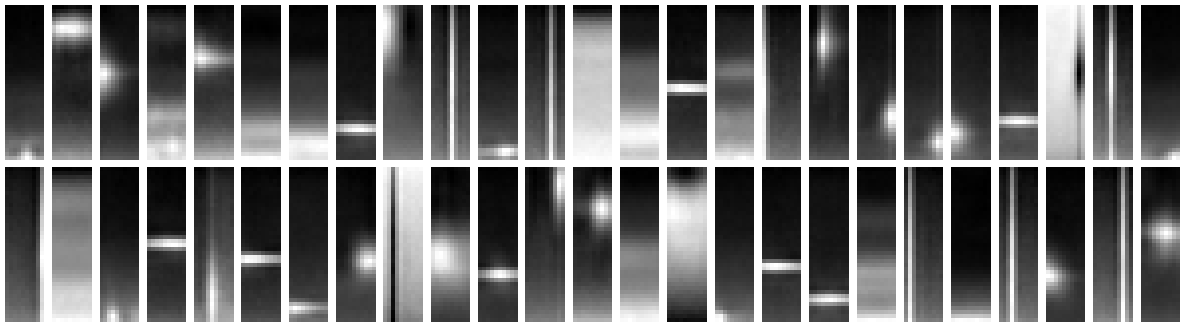
- The recordings consisted of bird sounds from $C = 19$ species, and the sounds were overlapping (with up to 6 birds in a single recording).
- There were altogether 645 ten-second audio clips.
- Half of the samples were used for model training, and the participants should predict the labels of the other half.
- We participated in the challenge, and our final submission placed 7th among the 77 teams.



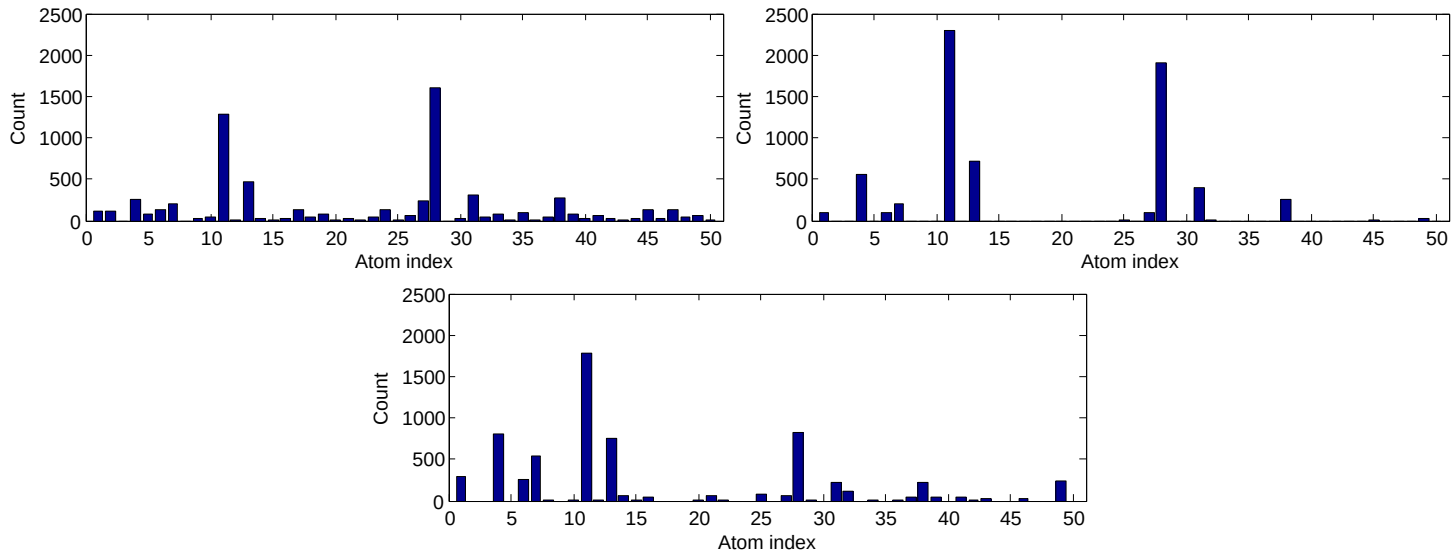
# IEEE MLSP2013 Birds — Our Method

- Our approach mixed six prediction models by averaging the predicted class probabilities together.
- Most fruitful model used dictionary based Bag-of-Words features.
  - Learn a dictionary of typical patches in the spectrograms (including the non-annotated ones).
  - Count the occurrences of each dictionary atom in each spectrogram.



# IEEE MLSP2013 Birds — Our Method

- Examples of patch histograms are shown below.
- Left: two bird species present, Right: no birds present, Bottom: a single bird present.
- One can spot the noise encoding patches (1, 4, 6, 7, 11 . . .), which are active in all histograms



# Summary

- The significance of Python as a language of scientific computing has exploded.
- Machine learning has been one of the key areas in this development.
- This has been coined by the open-access attitude of the community: licensing tends to be very free.
- One of the key benefits of `scikit-learn` is the uniform API: It's easy to test a wide range of algorithms with a short piece of code.
- Deep learning is a growing trend—powered by Python.