

Steps

- Frame the problem
- Data exploration
- Preprocess and feature selection
- Model development
- Final evaluation

Frame the problem

- What is your goal? Classification? Regression?
- What performance measure should you use?

Data Exploration

- After splitting your dataset (train/val/test?)
- Plot data
- See correlations
- Observe ranges of data

Preprocess and feature selection

Remember look only at the training data! Perform the same transformation on the validation/test

- Get a list of things to try (see if it improves or makes it worse):
 - Remove duplicate/unneeded features
 - Remove outliers
 - Drop rows with missing values or impute missing values (mean imputation, learn the value using regression, etc.)
 - Feature encoding by transforming categorical variables into numerical variables (e.g., nominal: one hot encoding, ordinal: label encoder)
 - Feature normalization (scaling)
 - Feature engineering: with domain knowledge, common transformations
 - Dimensionality reduction (PCA). We will discuss this topic in class.
 - If needed, deal with an imbalanced dataset

Model the dataset

- For each of your three approaches:
 1. Fit the model using:
 - different options you developed in the preprocessing stage or during the learning process
 - different hyper-parameter choices (regularization, etc.)
 2. Evaluate the fitted model with your criteria (accuracy, recall, precision, f1 score, etc., ...).
 3. See how you could improve your model.



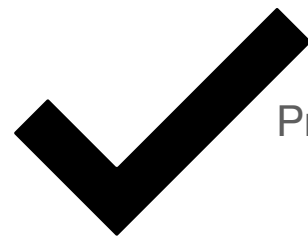
Experiment!

Finally

- Use your test set.

Read more at: <https://neptune.ai/blog/life-cycle-of-a-machine-learning-project>

1. Working with text

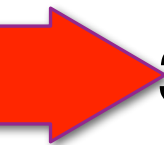


Previously posted

2. Working with unbalanced datasets



Previously posted



3. Hyperparameter tuning

4. Very will briefly discuss diagnosing errors

Ack!!! There are too
many parameters to
tune

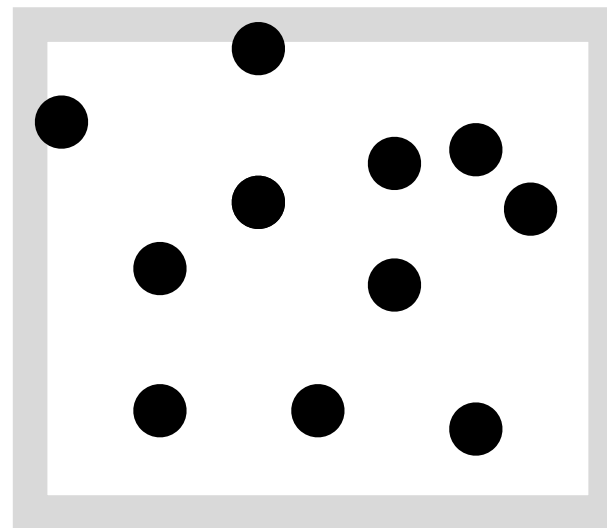
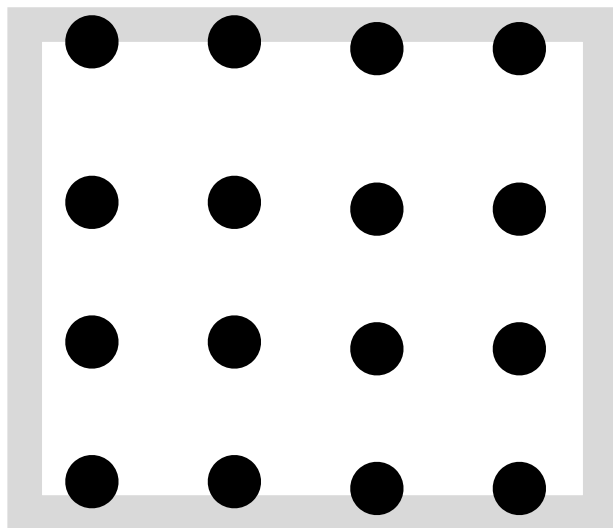
sklearn's [RandomizedSearchCV](#)
and [GridSearchCV](#) are classes for
parameter tuning that
methodically builds and evaluates
different combinations of
parameters as a grid

Two main approaches

Heuristics (not rules!)

If you have n hyperparameters, the search space is all the different values the n different hyperparameters can take. You can think of this as an n -dimensional volume.

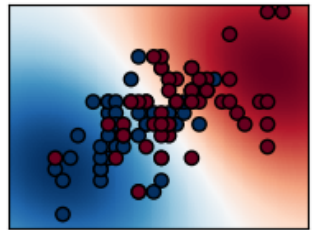
1. Grid search: create a grid on search space.
2. Random: randomly select items in the search space.



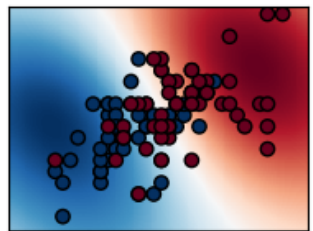
GridSearchCV

These also need to be imported

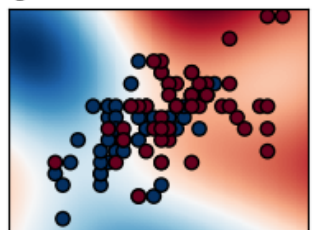
gamma=10⁻¹, C=10⁻²



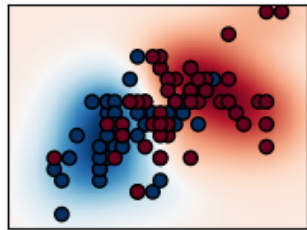
gamma=10⁻¹, C=10⁰



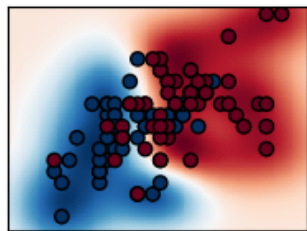
gamma=10⁻¹, C=10²



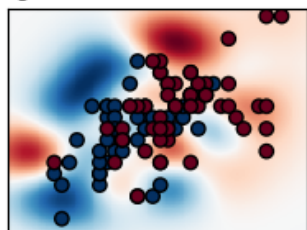
gamma=10⁰, C=10⁻²



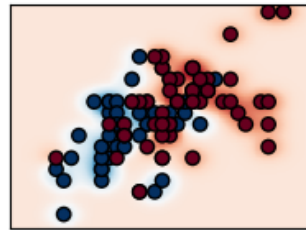
gamma=10⁰, C=10⁰



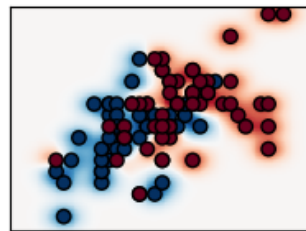
gamma=10⁰, C=10²



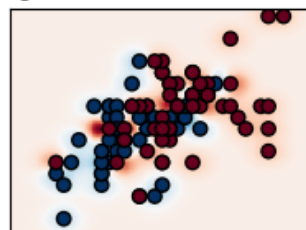
gamma=10¹, C=10⁻²



gamma=10¹, C=10⁰



gamma=10¹, C=10²



```
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import GridSearchCV
```

```
# Train classifiers
```

```
#
```

```
# For an initial search, a logarithmic grid with basis  
# 10 is often helpful. Using a basis of 2, a finer  
# tuning can be achieved but at a much higher cost.
```

```
C_range = np.logspace(-2, 1, 3)
gamma_range = np.logspace(-1, 1, 3)
param_grid = dict(gamma=gamma_range, C=C_range)
cv = StratifiedShuffleSplit(n_splits=5, test_size=0.2,
grid = GridSearchCV(SVC(), param_grid=param_grid, cv=cv)
grid.fit(X, y)
```

```
print("The best parameters are %s with a score of %0.2f"
      % (grid.best_params_, grid.best_score_))
```

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Example from http://scikit-learn.org/stable/auto_examples/svm/plot_rbf_parameters.html

Example uses:

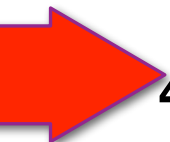
```
C_2d_range = [1e-2, 1, 1e2]
```

```
gamma_2d_range = [1e-1, 1, 1e1]
```

Learn more at:

[https://chrisalbon.com/code/machine_learning/model_selection/
hyperparameter_tuning_using_random_search/](https://chrisalbon.com/code/machine_learning/model_selection/hyperparameter_tuning_using_random_search/)

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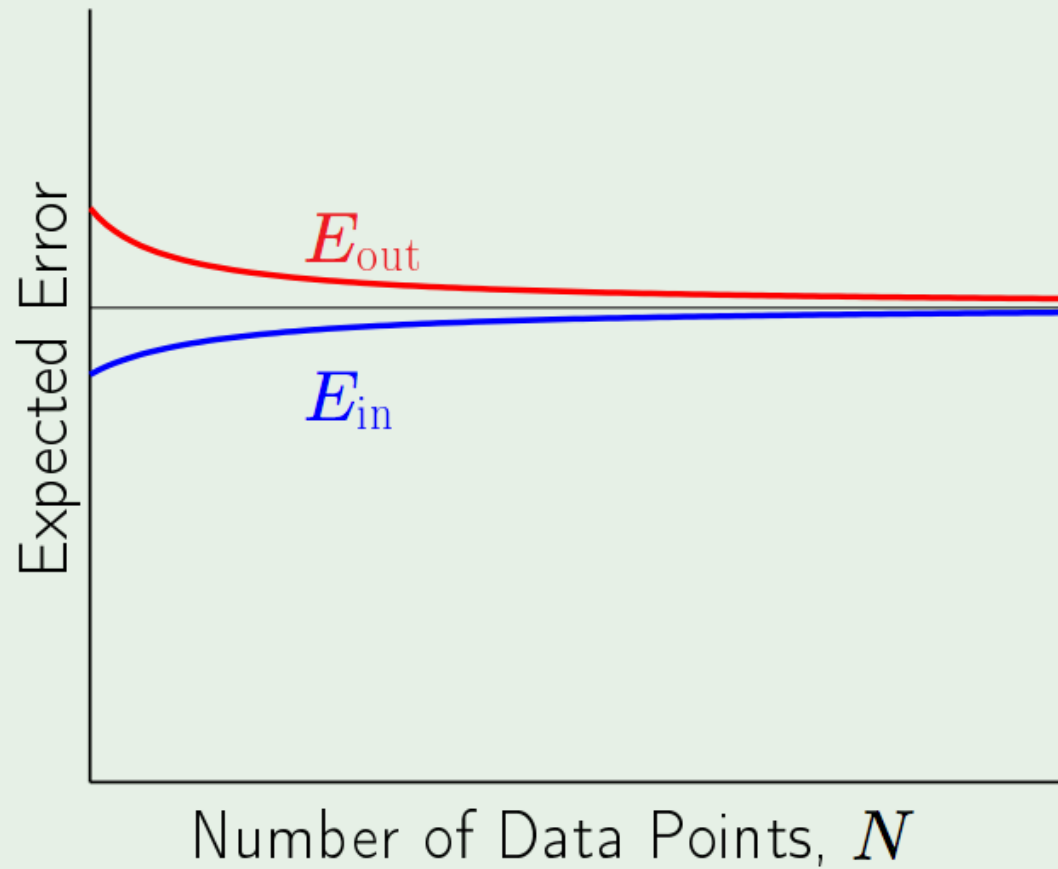
Improvements!

- Ideas:
 - Get more data
 - Add more features
 - perform feature reduction
 - Scale data (bin data, take the log of a feature, standardize, ...)
 - Regularize
 - Try a different model
 - Use more/fewer iterations/different learning rate
 - Use a different optimizer

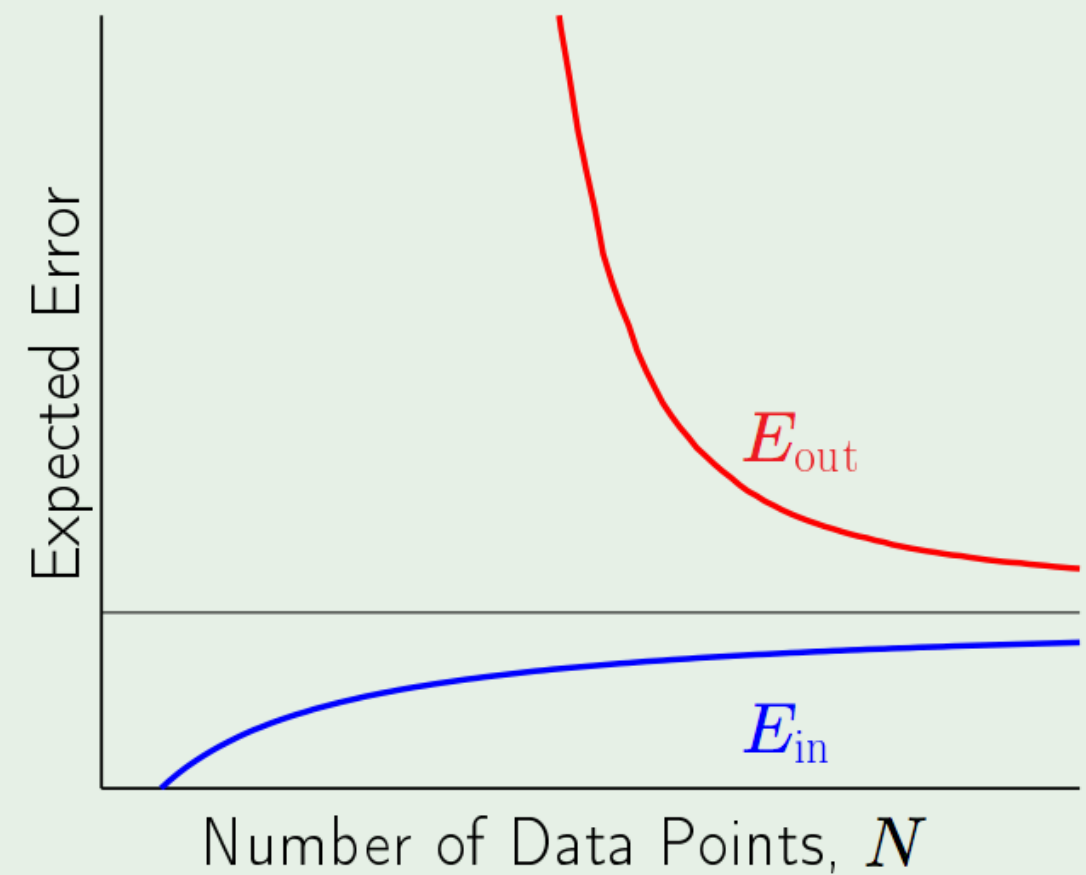
Bias vs Variance

- Run diagnostics
 - Overfitting - big gap between training and validation
 - Underfitting - high training error

The curves



Simple Model



Complex Model