

Lecture 7

End-to-End ML Project

From Data Collection to Deployment
Part 2

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Checklist: 8 Main steps

- **Frame the problem & Look at a bigger picture**
- **Get the data**
- **Discover and visualize data to gain insights**
- **Prepare the data for Machine Learning Algos**
- **Explore different models and short-list the best one**
- **Fine-tune your models and combine them a greater solution**
- **Present your Solution**
- **Launch, Monitor and Maintain your system**

Discussion so far (please check part 1...)

Data preparation

- Data cleaning → Removing outliers and drop the missing values
- Feature selection (optional step)
- Feature engineering
 - Feature discretization of continuous feature values
 - Feature decomposition
 - Feature transformation
 - Aggregate features into promising new features
- Feature scaling → standardize or normalize features

Topics to be covered

- **Explore different Machine Learning (ML) models**
- **Fine-tune each model**
- **Short-list the promising models or the best model**
- **Present your solution**

Machine Learning Models



```
graph TD; A[Machine Learning Models] --> B[Regression models]; A --> C[Classification models]
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Regression models

- Linear regression
- Polynomial regression
- SVM regression
- Random Forrest regression
- Regularized linear models
 - Ridge
 - Lasso
 - Elastic net

Classification models

- Logistic regression
- Support vector machine
- Decision tree
- Random Forrest
- Extra trees

Artificial NN

- Fully connected network
- CNN
- RNN (LSTM and GRU)



Prediction for both Regression and Classification is possible using NN

Fine-tune any model: Why this is required?

- To stop underfitting and overfitting
- To achieve better generalization
- Bias vs. Variance trade-off
(Error on both train set and test should be small)

Hyperparameter tuning and model selection

Two general options

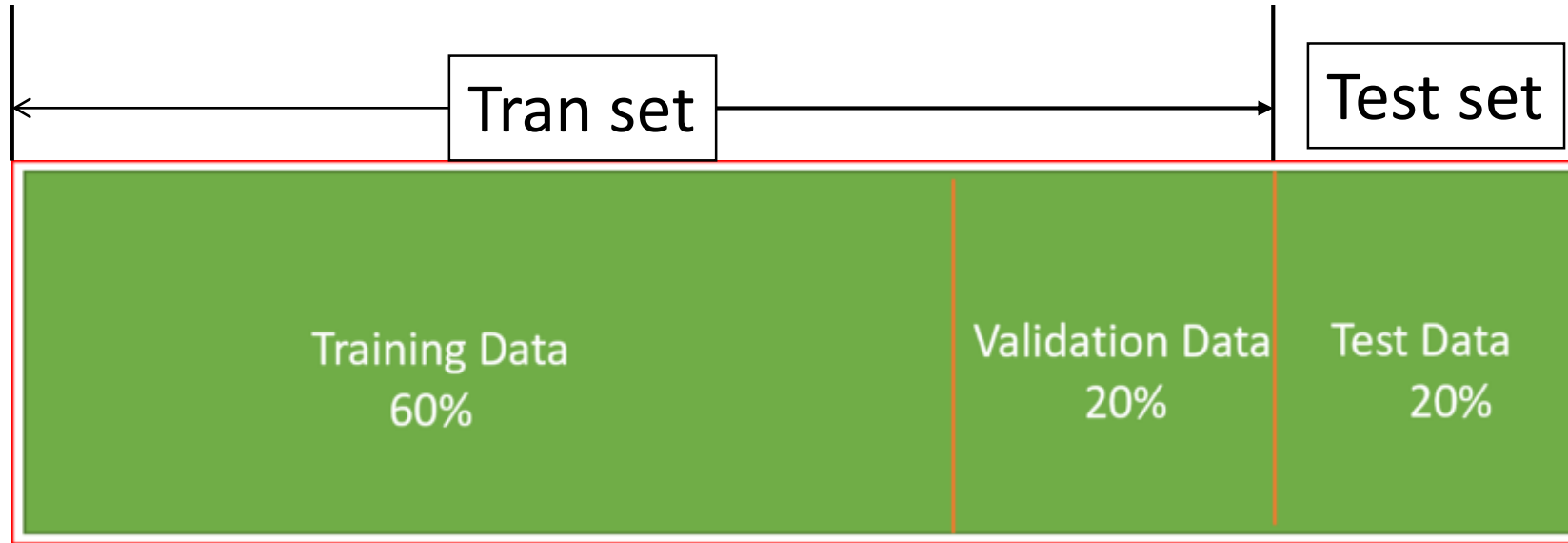
- Holdout validation
- K-fold Cross-validation

Holdout validation

Tip:

This data distribution depends on the size of the dataset

e.g.: if your dataset contains 10 Million instances, then holding out 1% data will be good enough.



Problems of Holdout validation

- Model evaluations will be imprecise and bad if the validation set is too small or too large.
- Due to *sample variability between training and test set*, the model may fail to generalize on test data. This leads to a low training error rate but a high test error rate.

**Held out validation set
(Dev set)**

K fold cross-validation

Option → Scikit-Learn's *GridSearchCV*

Split 1	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Metric 1
Split 2	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Metric 2
Split 3	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Metric 3
Split 4	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Metric 4
Split 5	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Metric 5

Training data

Test data

Hold-out vs. Cross-validation

- The hold-out method is good to use when you have a very large dataset, you're on a time crunch, or you are starting to build an initial model in your ML project.
- As cross-validation uses multiple train-test splits, it takes more computational power and time to run than using the holdout method.

Evaluation

- We got your tuned model (with set hyperparameters)
- You may try ensemble methods (optional) if you fine-tuned different ML models
- You must measure the performance of the model on the test set to estimate the generalization error and make evaluation based on judiciously chosen metrics associated with your ML problem.

Present your solution

- **Explain why and how your solution achieves the objective**
- **Describe what worked and what didn't**
- **List your assumptions and your system's limitations**