

AI Enterprise Workflow Study Group

Course 4, Week 1

4/18/2020

Agenda

- Check in
- Discussion
- Next steps

Course & Study Group Schedule

Al Enterprise Workflow Study Group					
Session	Topic	Date			
Overview Webinar	Webinar with instructor, Ray Lopez	15-Feb			
Course 1 Week 1	Course intro	22-Feb			
Course 1 Week 2	Data ingestion, cleaning, parsing, assembly	29-Feb			
Course 2 Week 1	Exploratory data analysis & visualization	7-Mar			
Course 2 Week 2	Estimation and NHT	14-Mar			
Course 3 Week 1	Data transformation and feature engineering	21-Mar			
Course 3 Week 2	Pattern recognition and data mining best practices	28-Mar			
Course 4 Week 1	Model evaluation and performance metrics	18-Apr			
Course 4 Week 2	Building machine learning and deep learning models	25-Apr			
Course 5 Week 1	Deploying models	2-May			
Course 5 Week 2	Deploying models using Spark	9-May			
Course 6 Week 1	Feedback loops and monitoring	16-May			
Course 6 Week 2	Hands on with OpenScale and Kubernetes	23-May			
Course 6 Week 3	Captsone project week 1	30-May			
Course 6 Week 4	Captsone project week 2	6-Jun			



Course 4 Week 1 learning objectives

- 1. Discuss common regression, classification, and multilabel classification metrics
- 2. Describe common strategies for grid searching and cross-validation
- 3. Explain the use of linear models in supervised learning applications
- 4. Create and test an instance of Watson Natural Language Understanding
- 5. Employ evaluation metrics to select models for production use

Regression Metrics

RMSE =
$$\sqrt{\frac{1}{N} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}$$

MAE

$$MAE = \frac{1}{N} \sum_{i=1}^{n} |\hat{y}_i - y_i|$$

sklearn.metrics.mean_squared_error

sklearn.metrics.mean_absolute_error

RMSE vs MAE

- Both same units as data
- RMSE penalizes large errors
- RMSE differentiable

ASE 1: Evenly distributed errors			CASE 2: Small variance in errors			CASE 3: Large error outlier					
ID	Error	Error	Error^2	ID	Error	Error	Error^2	ID	Error	Error	Error^2
1	2	2	4	1	1	1	1	1	0	0	0
2	2	2	4	2	1	1	1	2	0	0	0
3	2	2	4	3	1	1	1	3	0	0	0
4	2	2	4	4	1	1	1	4	0	0	0
5	2	2	4	5	1	1	1	5	0	0	0
6	2	2	4	6	3	3	9	6	0	0	0
7	2	2	4	7	3	3	9	7	0	0	0
8	2	2	4	8	3	3	9	8	0	0	0
9	2	2	4	9	3	3	9	9	0	0	0
10	2	2	4	10	3	3	9 ,	10	20	20	400
		MAE	RMSE			MAE	RMSE			MAE	RMSE
		2.000	2.000			2.000	2.236			2.000	6.325

Classifier Metrics

Recall from C3W1:

		True cond	dition			
	Total population	Condition positive	Condition negative	$= \frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Σ True positi	racy (ACC) = ve + Σ True negative al population
Predicted condition	Predicted condition positive	True positive	False positive, Type I error	Positive predictive value (PPV), Precision = Σ True positive Σ Predicted condition positive	False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$	
	Predicted condition negative	False negative, Type II error	True negative	False omission rate (FOR) = Σ False negative Σ Predicted condition negative	Negative predictive value (NPV) = Σ True negative Σ Predicted condition negative	
		True positive rate (TPR), Recall, Sensitivity, probability of detection, Power = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	Positive likelihood ratio (LR+) = TPR FPR	Diagnostic odds ratio	F ₁ score =
		False negative rate (FNR), Miss rate $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	Negative likelihood ratio (LR-) = FNR TNR	$(DOR) = \frac{LR+}{LR-}$	2 · Precision · Recall Precision + Recall



F_{β} Score

Combines precision and recall into one metric

- Precision = $\frac{TP}{TP+FP}$: proportion called true that are correct
- Recall = $\frac{TP}{TP+FN}$: proportion of true that are called correctly

The F1_score is the harmonic mean of precision and recall.

$$F1_score = \frac{\frac{2}{1}}{\frac{1}{recall} + \frac{1}{precision}}$$

The F1_score is actually a special case of the F_{β} score, where the weight of recall and precision is evenly balanced. The F-score can also be written as:

$$F_{\beta} = (1 + \beta^2) \frac{\text{precision} \times \text{recall}}{(\beta^2 \times \text{precision}) + \text{recall}}$$

β essentially a multiplier on importance of recall



Model Validation

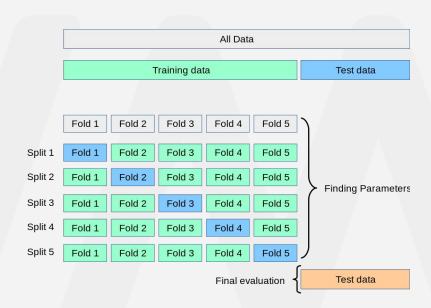
K-Fold Validation

- Shuffle & Split: Shuffles before split
- Stratified: Balance classes across folds

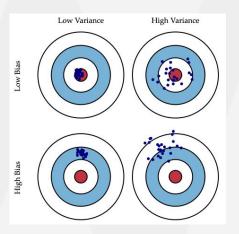
Parameter Tuning

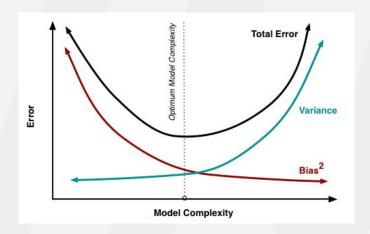
- Grid, random search
- Also Bayesian methods





Bias vs Variance





Good article: http://scott.fortmann-roe.com/docs/BiasVariance.html

Linear Models

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Linear Models in Python

    LinearRegression (sklearn.linear model.LinearRegression)

        LogisticRegression (sklearn.linear model.LogisticRegression)

    RidgeCV (sklearn.linear model.RidgeCV)

    LassoCV (sklearn.linear_model.LassoCV)

    MultiTaskLasso (sklearn.linear model.MultiTaskLasso)

    ElasticNetCV (sklearn.linear model.ElasticNetCV)

    BayesianRidge (sklearn.linear model.BayesianRidge)

      • statsmodels (for GLMs and situations where inference is the goal)

    PyMC3 (for GLMMs)

            from sklearn import linear model
             slide print([lm for lm in dir(linear model) if not re.search(" ",lm)])
                 'LassoCV', 'LassoLars', 'LassoLarsCV', 'LassoLarsIC', 'LinearRegression', 'Log', 'LogisticRegression', 'LogisticRegression'
'ModifiedHuber', 'MultiTaskElasticNet', 'MultiTaskElasticNetCV', 'MultiTaskLasso', 'MultiTaskLassoCV', 'OrthogonalMatchin
```



Additional Discussion

What did you learn?

What stumbling blocks did you run into?

How do these lessons relate to your experience?

What did you learn/find interesting in this week's lesson?

What are you doing as homework?

What interesting resources have you found?

Other?

