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ML Cheatsheet #1

Your practical 7-step guide from business idea to a deployable regression model

A Foundational Guide for Aspiring Data Scientists

Based on
"Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow"
by

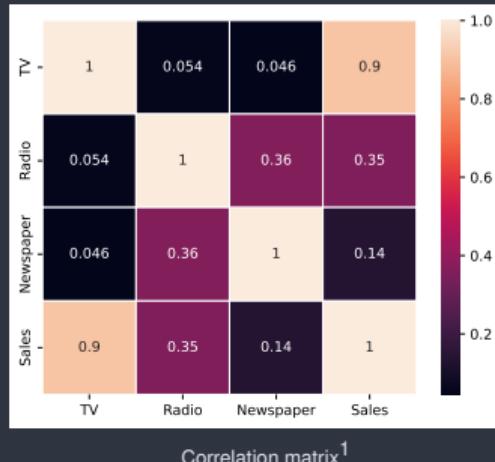
Aurélien Géron

Step 1: Properly Frame the Problem

Steps 2 & 3: Acquire and explore the data

Possible data sources:

- public, open data repository (e.g., Kaggle, UCI)
- first-party data (e.g., company, operational data)
- online sources (e.g., web scraping, APIs)



```
1 import kagglehub
2 from kagglehub import KaggleDatasetAdapter
3
4 # Loading a DataFrame from Kaggle
5 adsSales = kagglehub.dataset_load(
6     KaggleDatasetAdapter.PANDAS,
7     "thorgodofthunder/
8     tvradionewspaperadvertising/versions/1",
9     "Advertising.csv",)
```

Exploratory data analysis (EDA)

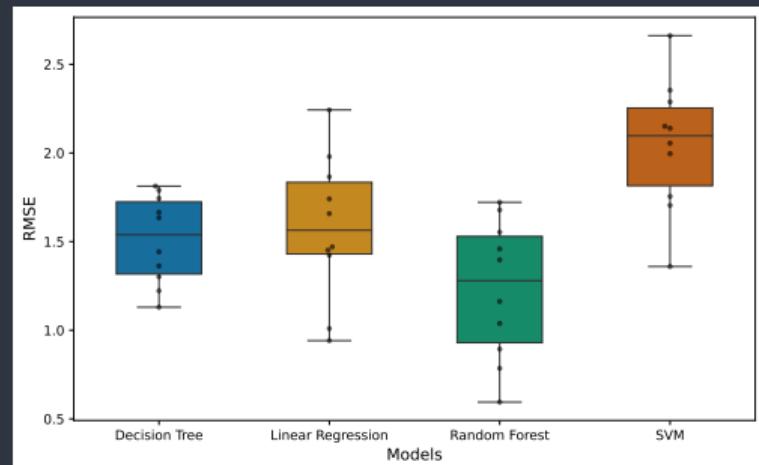
1. split data into train & test sets
2. investigate correlation (numeric attributes)
3. transform data using pipelines (e.g., imputation, one-hot-encoding)

Source of "Advertising sales data":
www.kaggle.com/datasets/thorgodofthunder/tvradionewspaperadvertising

Step 4: Train & evaluate candidate models

Candidate models (Regression)	Advantages	Disadvantages
Linear regression	simple, interpretable, fast to train	assumes linearity, sensitive to outliers & multicollinearity
Decision tree regressor	models non-linearity, easy to visualize & interpret	prone to overfitting, sensitive to data change & skewness
Support vector regression (SVR)	models non-linearity, effective for high-dimensional & medium-sized data	Computationally expensive, difficult to interpret & sensitive to kernel choice

```
1 # Training a linear regression model
2
3 from sklearn.linear_model import LinearRegression
4 from sklearn.metrics import mean_squared_error
5 import numpy as np
6
7 lin_reg = LinearRegression()
8 lin_reg.fit(adsSales_prepared, adsSales_labels)
9
10 adsSales_predictions = lin_reg.predict(
11     adsSales_prepared)
12 lin_mse = mean_squared_error(adsSales_labels,
13     adsSales_predictions)
14 lin_rmse = np.sqrt(lin_mse)
```



Root mean squared scores of candidate models

Step 5 : Fine-tune best model

Model hyper-parameters are fine-tuned to improve its performance:

1. explore large space with Random search
2. fine tune search with Grid search
3. use cross-validation in both cases

```
1 # Hyper-parameters tuning using grid search
2
3 from sklearn.model_selection import GridSearchCV
4
5 param_grid = [
6     {'n_estimators': [3, 10, 30, 50], 'max_features': [6, 8, 10]},
7     {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
8 ]
9
10 forest_reg = RandomForestRegressor()
11 grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
12                             scoring='neg_mean_squared_error',
13                             return_train_score=True)
14
15 # Fit model for all combinations of parameters
16 grid_search.fit(adsSales_prepared, adsSales_labels)
17
18 # Picking best model from grid search
19 final_model = grid_search.best_estimator_
```

Step 6: Assess final model performance on unseen test set

Prepare test set with same pipeline as the training set

```
1 # Defining test dataset
2 X_test = strat_test_set.drop("Sales", axis=1)
3 y_test = strat_test_set["Sales"].copy()
4
5 X_test_prepared = full_pipeline.transform(X_test)
```

Evaluate model performance

```
1 # Running predictions on test set
2
3 final_predictions = final_model.predict(X_test_prepared)
4
5 final_mse = mean_squared_error(y_test, final_predictions)
6 final_rmse = np.sqrt(final_mse)
```

Step 7: Save model for possible deployment

```
1 # Saving the model as joblib file
2
3 def save_model(model, name="model", model_path="."):
4     """
5         Save the model with a given name to a specific location.
6
7     Parameters
8     -----
9     model :
10        The model trained.
11     name:
12        The file name with which to save the model
13     model_path:
14        The path in which the model is saved
15     Example:
16        "./models/"
17
18     """
19     os.makedirs(model_path, exist_ok=True)
20     model_name = name + ".pkl"
21     pkl_path = os.path.join(model_path, model_name)
22     joblib.dump(model, pkl_path)
23
24 MODEL_PATH = os.path.join("models", "adsSales")
25 save_model(final_model, name="Random_forest_V1.1", model_path=MODEL_PATH)
```

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How do you choose your candidate models for regression?

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