dm25s1

Topic 06 : Data Modelling

Part 02 : Column Encoding

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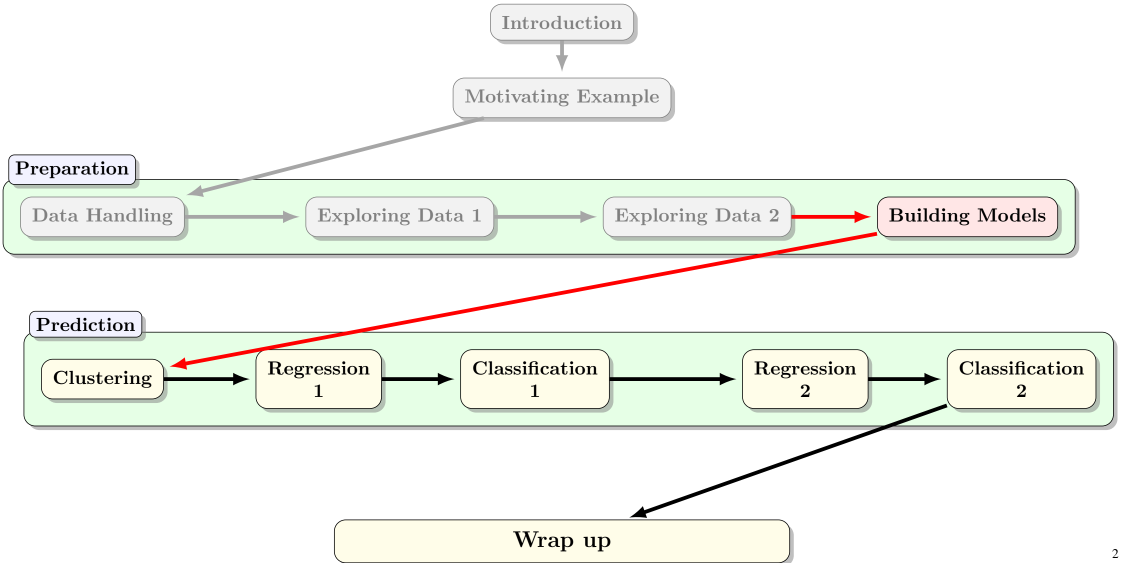
Autumn Semester, 2025

Outline

- Encoding categorical features, using pandas
- Looking ahead to feature preparation
- Overview of ML and what we have achieved

Data Mining (Week 6)



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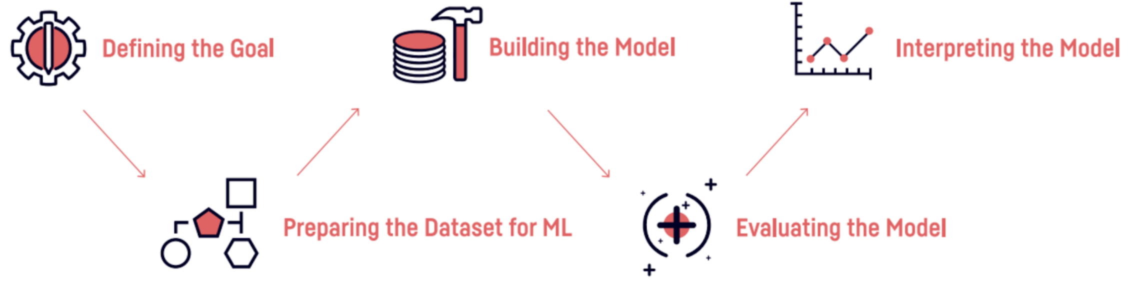
The Pipeline Metaphor

Model Building Pipeline



Source: Dataiku

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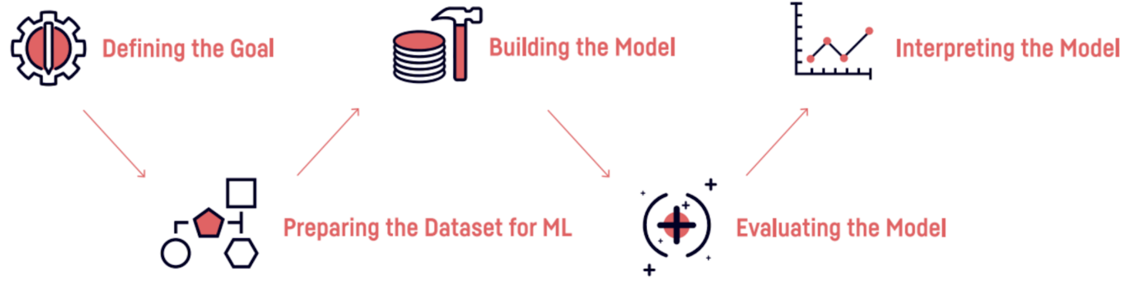

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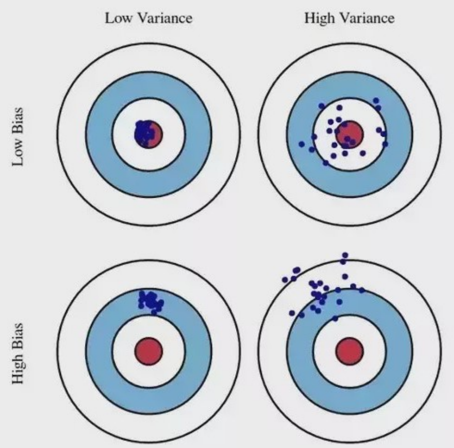
Comments

- We saw the first two stages in previous weeks
- This week we look at the remaining stages
- Of course this pipeline is a simplification. In reality it is iterative.

Bias-Variance and Total Error



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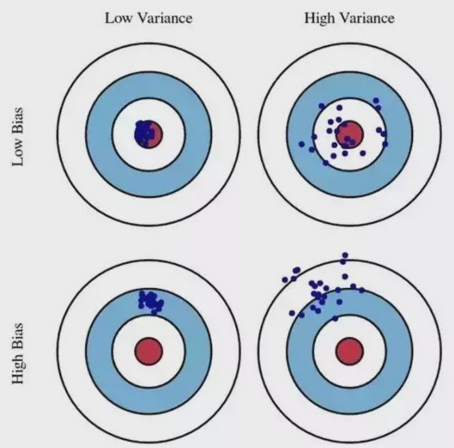

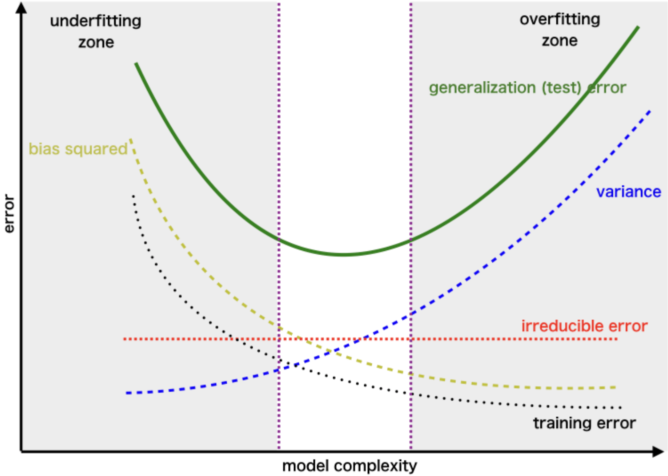

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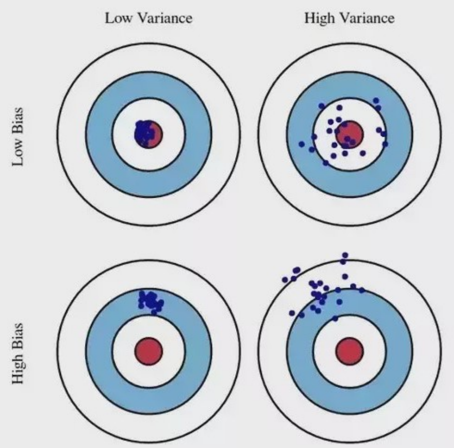

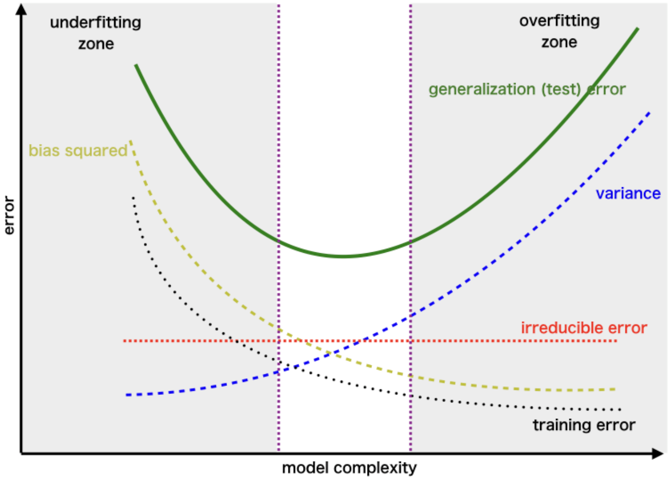

Look for parameters ***a*** that minimise the generalization error (estimated using the test set that was not used during training)

Example Model Types

Model	Applications	Concerns
Logistic Regression	X-ray classification	Regression with transformed variable
Fully connected networks	Classification	Classical ANN: choose encoding and size
Convolutional Neural Networks	Image processing	deep learning - choose segmentation
Recurrent Neural Networks	Voice recognition	ANN with feedback - how much?
Random Forest	Fraud Detection	Ensemble method - how many?
Reinforcement Learning	Learning by trial and error	Choose goal and penalties
Generative Models	Text, Image creation	Choose parameters
K-means	Segmentation	Choose distance function and k
k-Nearest Neighbors	Recommendation systems	Choose distance function and k
Bayesian Classifiers	Spam and noise filtering	Deal with imbalances

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Given the following fragment of a dataset, where the goal is to predict the salary of employees in a large organisation:

```
df = pd.read_csv('data/team.csv',\
        index_col="Name")
df
```

	Role	Skilled	Salary
Name			
Alice	Designer	Yes	40000
Bob	Programmer	No	25000
Carol	Tester	No	30000

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How can this data be represented by a linear model, where all quantities must take numeric values?

Using pandas .getdummies() on a binary-valued column

```
dfSkilledDummies = pd.get_dummies(df['Skilled'],\
        prefix='Skilled',\
        dtype=int)
dfSkilledDummies
```

	Skilled_No	Skilled_Yes
Name		
Alice	0	1
Bob	1	0
Carol	1	0

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Note that a binary-valued column becomes 2 dummy columns

Reducing redundancy (by 1) in 2 dummy columns

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dfSkilledIndicators = pd.get_dummies(df['Skilled'],\
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	IsSkilled
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```

	IsSkilled
Name	
Alice	1
Bob	0
Carol	0

A single indicator column can replace a group of 2 dummy columns

Using pandas .getdummies() on a multi-valued column

```
dfRoleDummies = pd.get_dummies(df['Role'],\
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        dtype=int)
dfRoleDummies
```

	Role_Designer	Role_Programmer	Role_Tester
Name			
Alice	1	0	0
Bob	0	1	0
Carol	0	0	1

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	Role_Designer	Role_Programmer	Role_Tester
Name			
Alice	1	0	0
Bob	0	1	0
Carol	0	0	1

Note that an n-valued column becomes n dummy columns

Reducing redundancy (by 1) in n dummy columns

```
dfRoleIndicators = pd.get_dummies(df['Role'],\
        prefix='Role',\
        drop_first=True,\
        dtype=int)\
        .rename(columns={\
        "Role_Programmer": "IsProgrammer",\
        "Role_Tester": "IsTester"})
dfRoleIndicators
```

	IsProgrammer	**IsTester**
Name		
Alice	0	0
Bob	1	0
Carol	0	1

Reducing redundancy (by 1) in n dummy columns

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dfRoleIndicators = pd.get_dummies(df['Role'],\
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	IsProgrammer	IsTester
Name		
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$n-1$ indicator columns can replace a group of n dummy columns

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- Build the model using the features in F.

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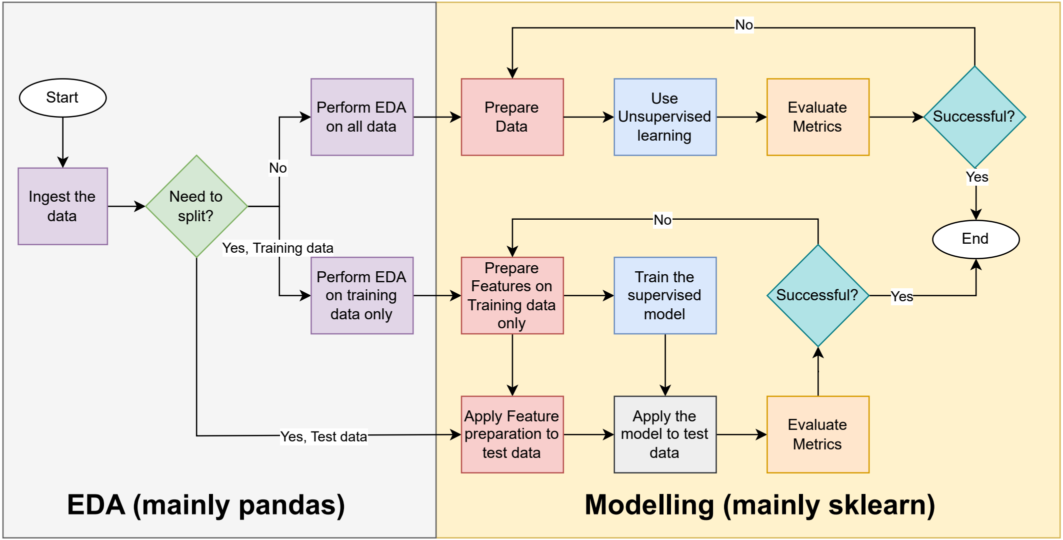
4. How can we reverse the operation (i.e., return from (0,1)-valued columns to categorical columns)?

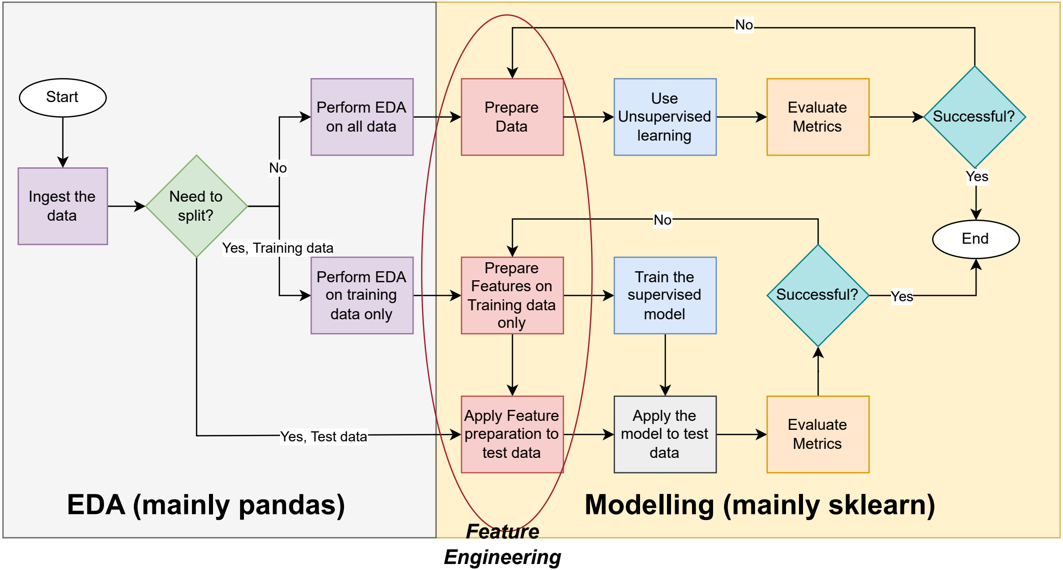
Outline

An overview of Machine Learning



On first glance, this might seem overwhelming, but note that the boxes are colour-coded, so that related

Where feature preparation fits. . .



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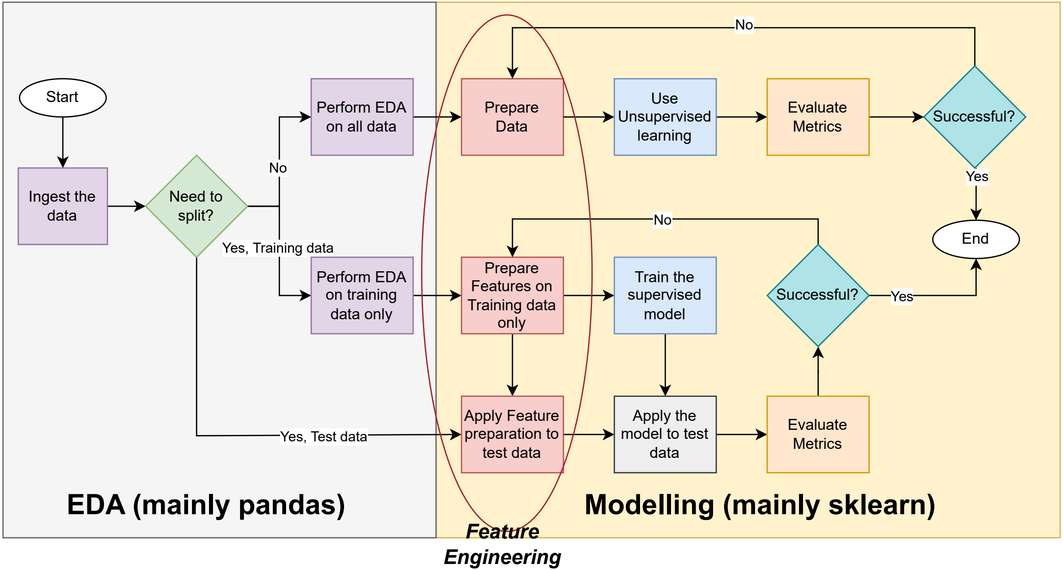

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- Can also rescale numerical columns, or encode more exotic columns (other datatypes, computed columns, . . .)
- As seen in the schematic, if an ML procedure is unsuccessful, more feature engineering should be considered - it can help.

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- In subsequent weeks we will put this theory into practice.

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Resources

- **A Summary of the Basic Machine Learning Models**
  `towardsdatascience.com/a-summary-of-the-basic-machine-learning-models-e0a65627ecbe`

- **Train-Test Split for Evaluating Machine Learning Algorithms**
  `https://machinelearningmastery.com/`
  `train-test-split-for-evaluating-machine-learning-algorithms`
  This week I have focused on the theory rather than its (python) implementation. This is a nice article that covers the implementation side of things.

- **Cross-Validation: Estimator Evaluator**
  `medium.com/swlh/cross-validation-estimator-evaluator-897d28afb4ff`
  Nice article that covers cross-validation in a lot more detail — we will be using many of these variants in later weeks, especially k-fold stratified.