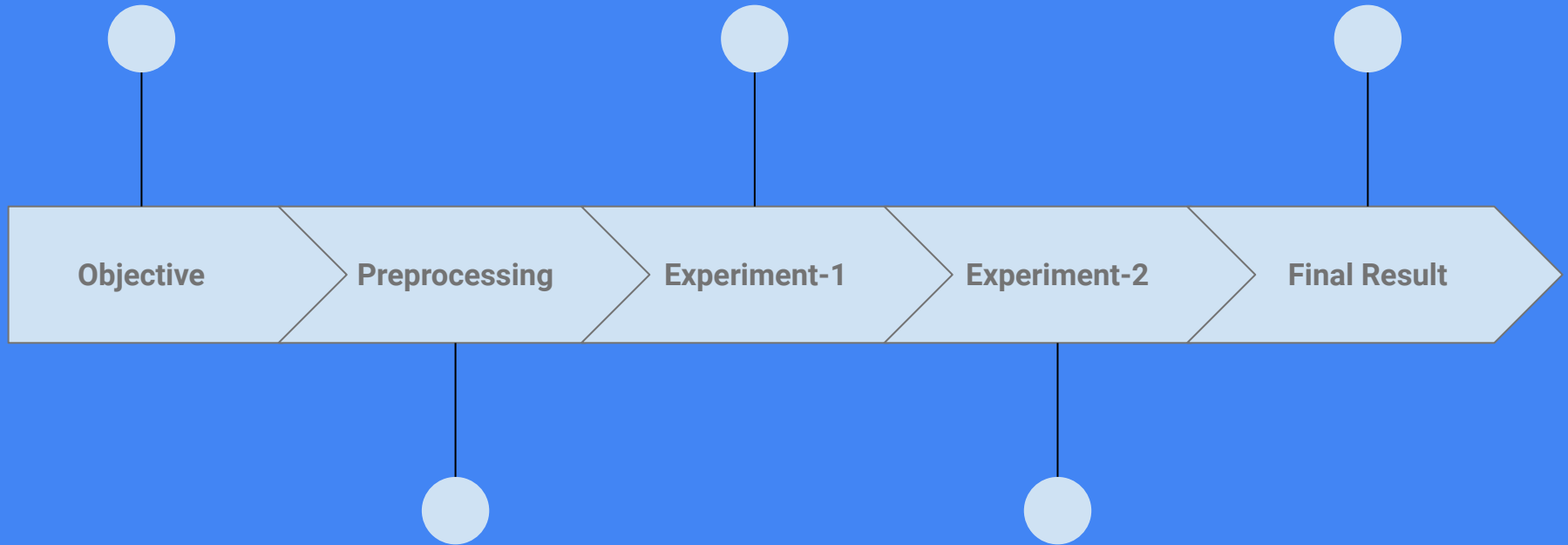


Prediction of German House Prices

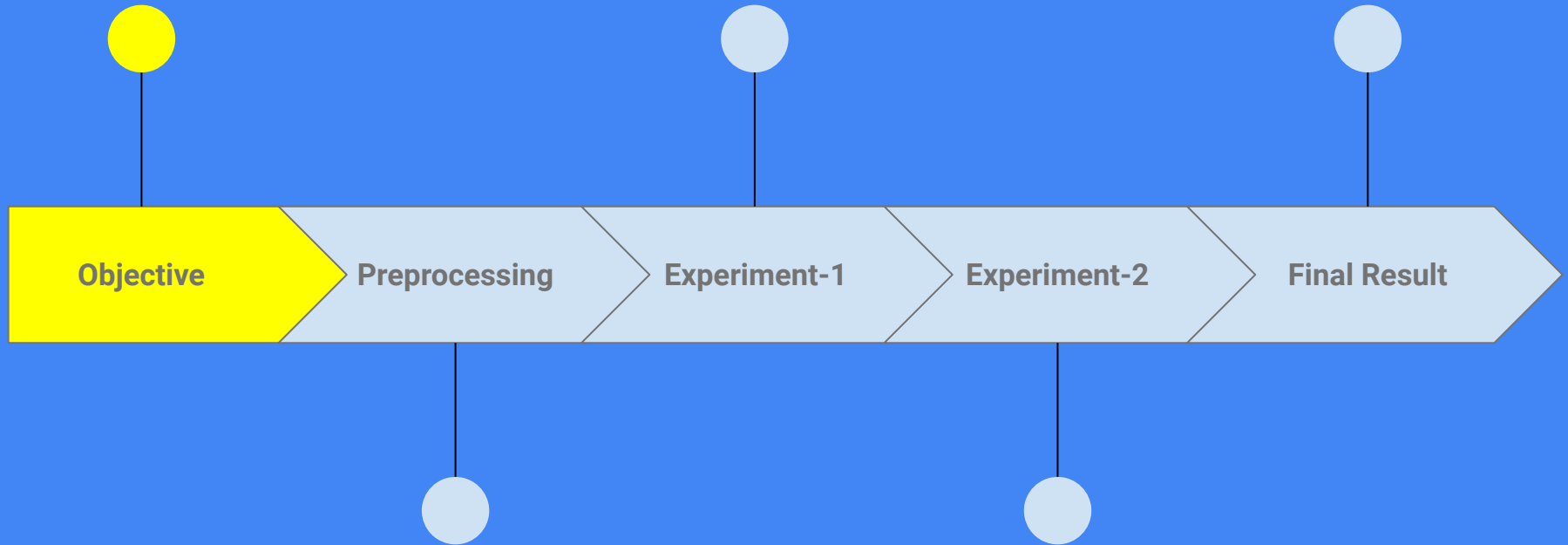
Knowledge Discovery (CENG-542)
Project Presentation



TOC



TOC



Objective

Objective: find patterns to determine prices for German houses based on different attributes

Problem: Regression of prices

Dataset: [germany_housing_data_14.07.2020](#) (10552 rows, 24 columns)

Tools: Python + Libraries



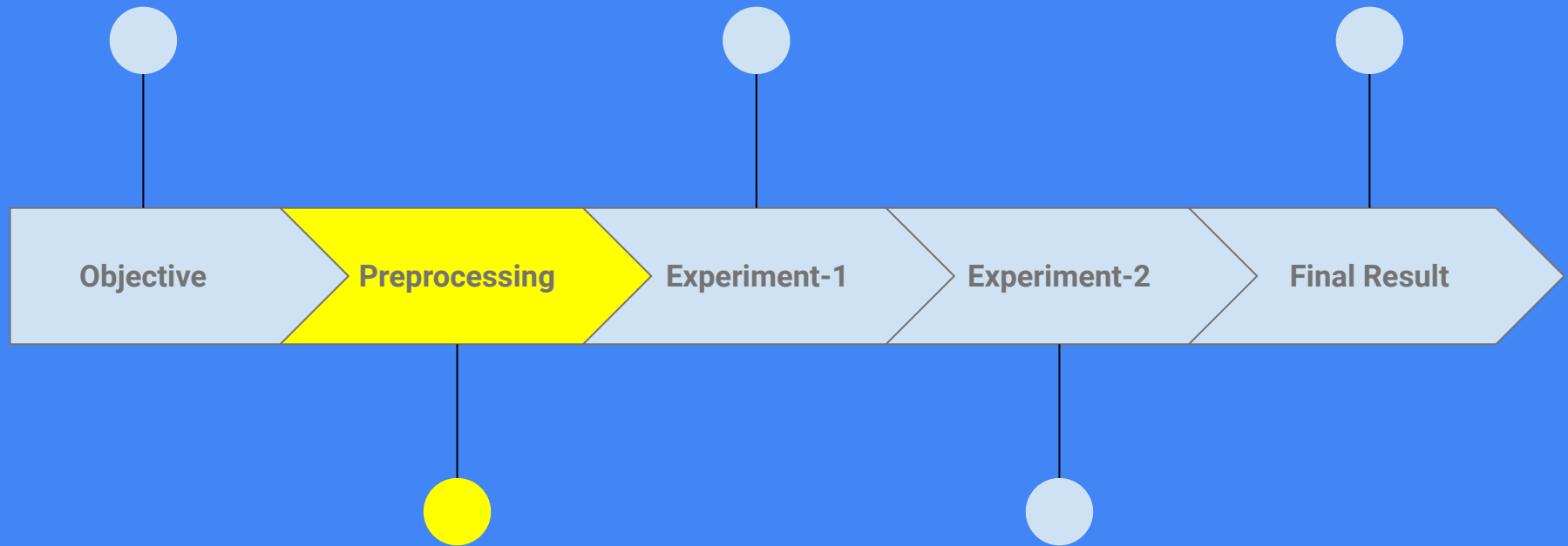
Getting to Know the Data

Dimension: 10552 x 25 (rows x columns)

Statistical Properties for Price: min = 0, mean = 556 685 , max = 13 000 000

3 Samples of dataset:

Type	Living_space	Lot	Usable_area	Bathrooms	Rooms	Year_built	State	...	Price
Mid-terrace house	140.0	890.0	NaN	3.0	4.0	1989.0	Sachsen	275000.0
Mid-terrace house	130.00	401.0	200.00	1	4	2014	Berlin	...	840000.0
Single dwelling	129.0	157.0.0	39.0	2.0	4.0	2018.0	Bayern	1075000.0



Preprocessing (a)

(1) Data Reduction (Dimensionality Reduction)

Drop features which have ...

- ... same information (State > City > Place)
- ... > 33.333% NaN values (7 of 24 features)

(2) Data Cleaning (Missing Data)

Replace all remaining NaN values with **mode**

	nulls_amount	nulls_percentage
Energy_consumption	8119	76.94
Year_renovated	5203	49.31
Usable_area	4984	47.23
Energy_efficiency_class	4819	45.67
Bedrooms	3674	34.82
Free_of_Relation	3569	33.82
Energy_certificate_type	3526	33.42
Furnishing_quality	2726	25.83
Floors	2664	25.25
Garages	1960	18.57
Garagetype	1960	18.57
Bathrooms	1801	17.07
Energy_source	1227	11.63
Energy_certificate	755	7.16
Year_built	694	6.58
Heating	584	5.53
Type	402	3.81
Condition	323	3.06
Place	290	2.75
State	1	0.01
City	1	0.01
Price	0	0.00
Rooms	0	0.00
Lot	0	0.00
Living_space	0	0.00
Unnamed: 0	0	0.00

Figure 0 – NaN values in Dataset

Preprocessing (b)

(3) Data Cleaning (Outlier Removal)

removed 966 outliers using z-score ($z > 3$) and fixed price range of [50 000, 10 000 000]

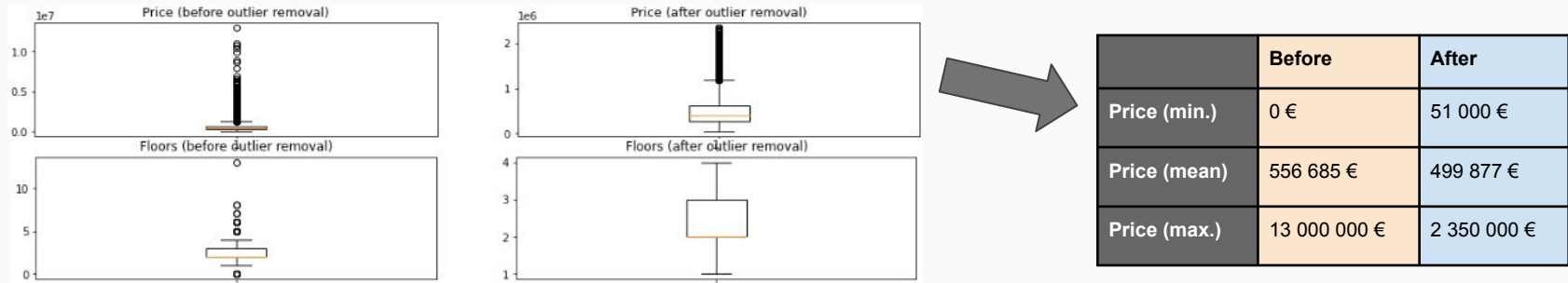


Figure 1 - Effect of Outlier Detection

Preprocessing (c)

(4) Data Transformation (One-hot encoding)

all categorical data got one-hot encoded

17 features → 170 features

(5) Data Reduction (Feature Selection)

Select only features with corr. factor ≥ 0.2

Feature	Living_space	Furnishing_quality_luxus	Bathrooms	Type_Villa	Rooms
Cor. factor	0.44	0.32	0.27	0.27	0.25

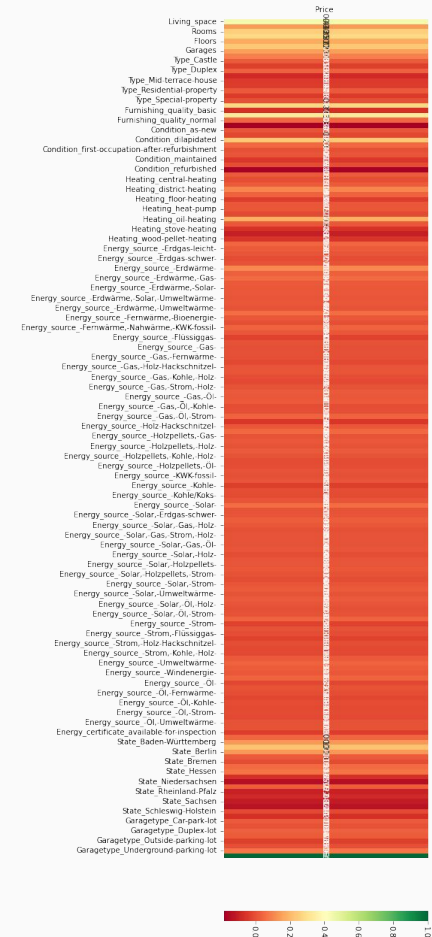
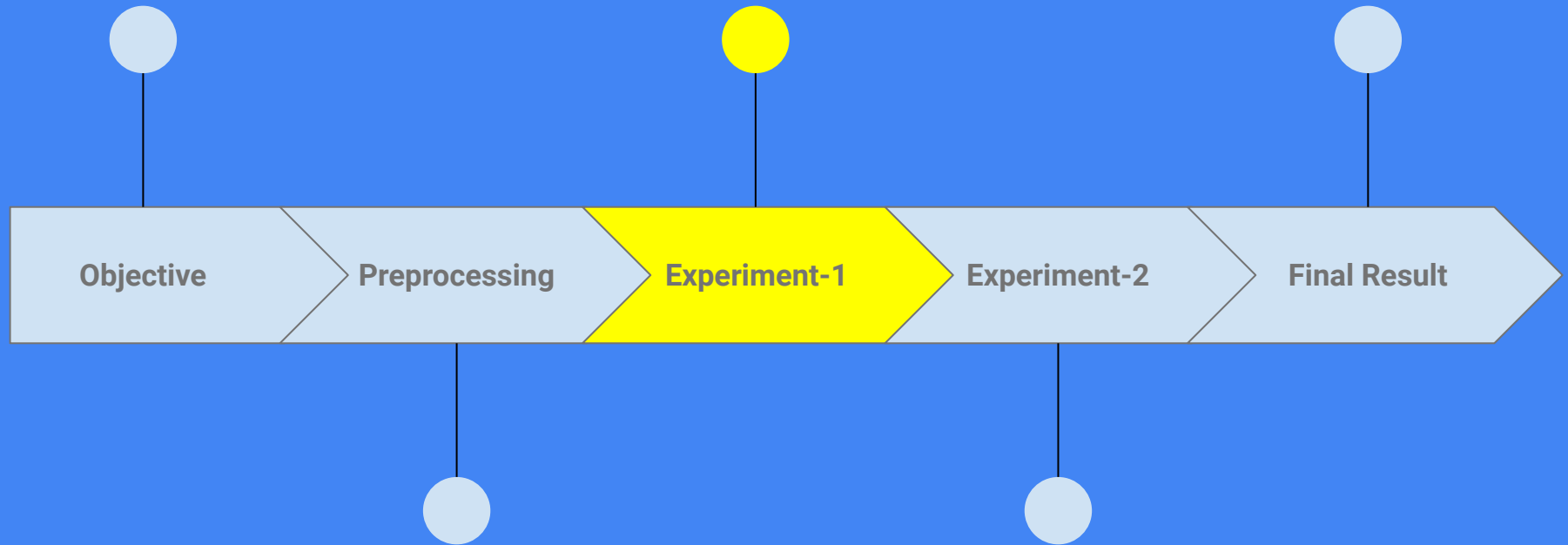


Figure 2 - Correlation Heatmap



Experiment-1

Procedure: linear regression models are trained, each on a different feature (80%, 20% data split)

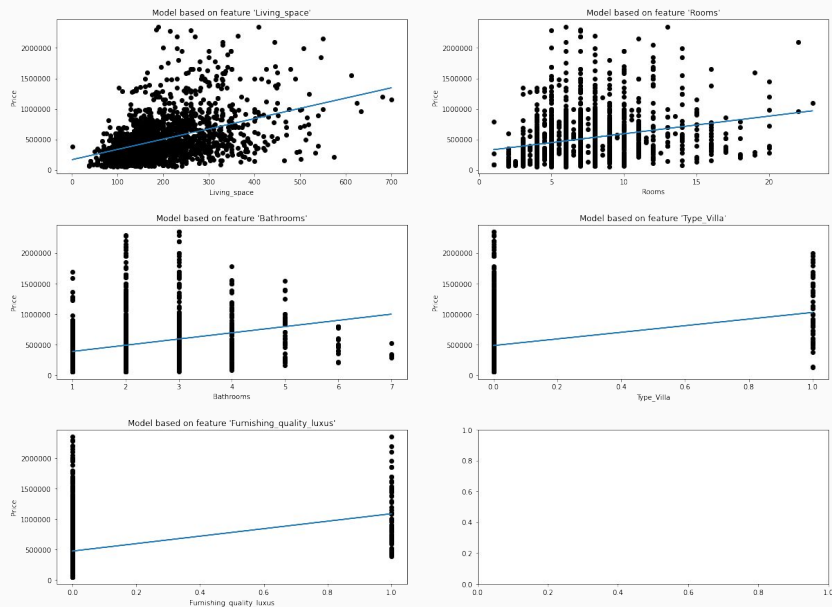


Figure 3 - Univariate Linear Regression Models

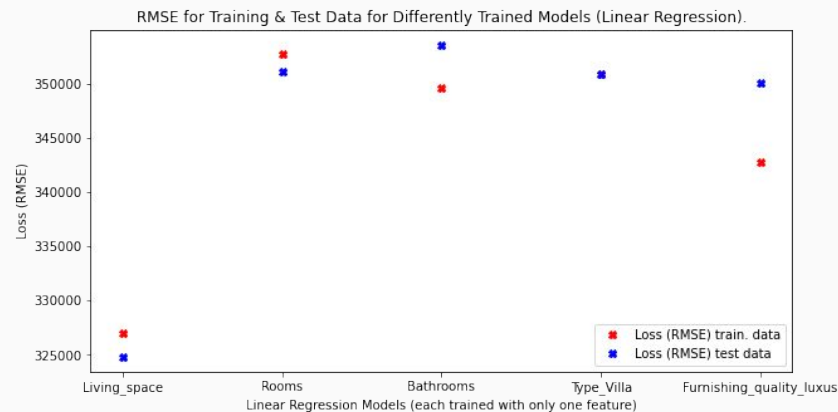
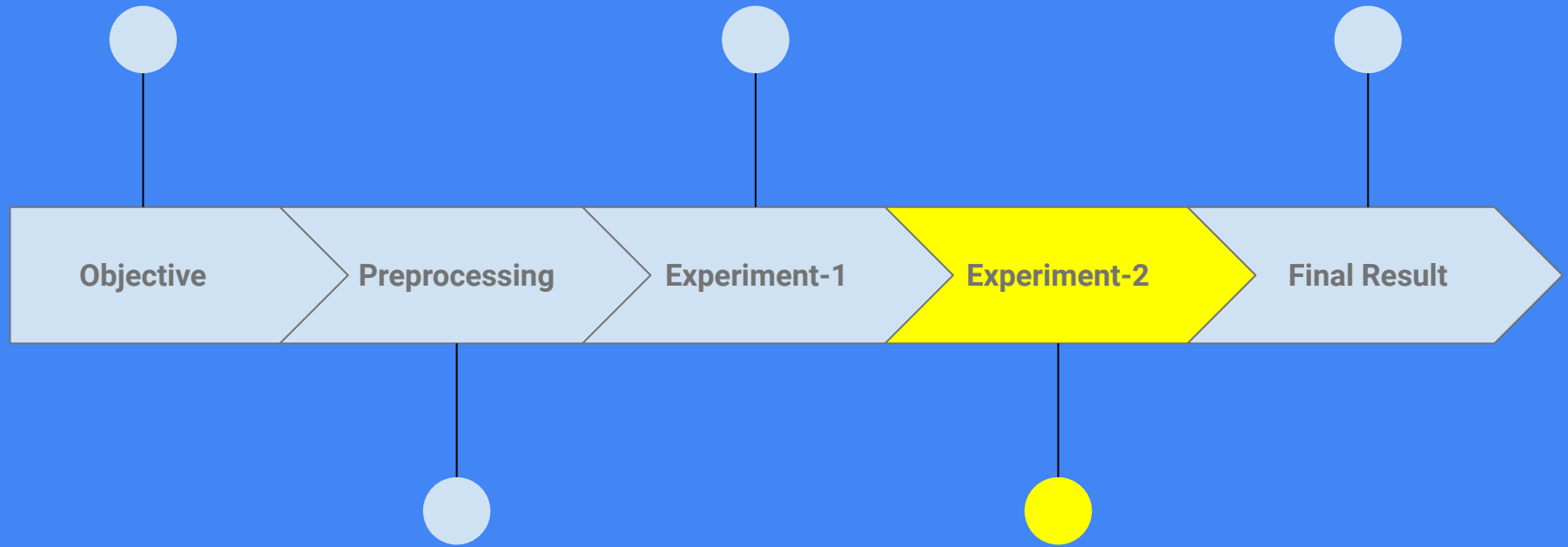


Figure 4 – Root-Mean-Squared-Errors



Experiment-2

Learning Algorithms:

- (1) Linear Regression
- (2) K-nearest-neighbors (Regressor)
- (3) Random Forest (Regressor)

Procedure:

For each learning algorithm try different amount of features: 1, 2, 3, 4, 5, or 170 (all)

→ $3 * 6 = 18$ machine learning models

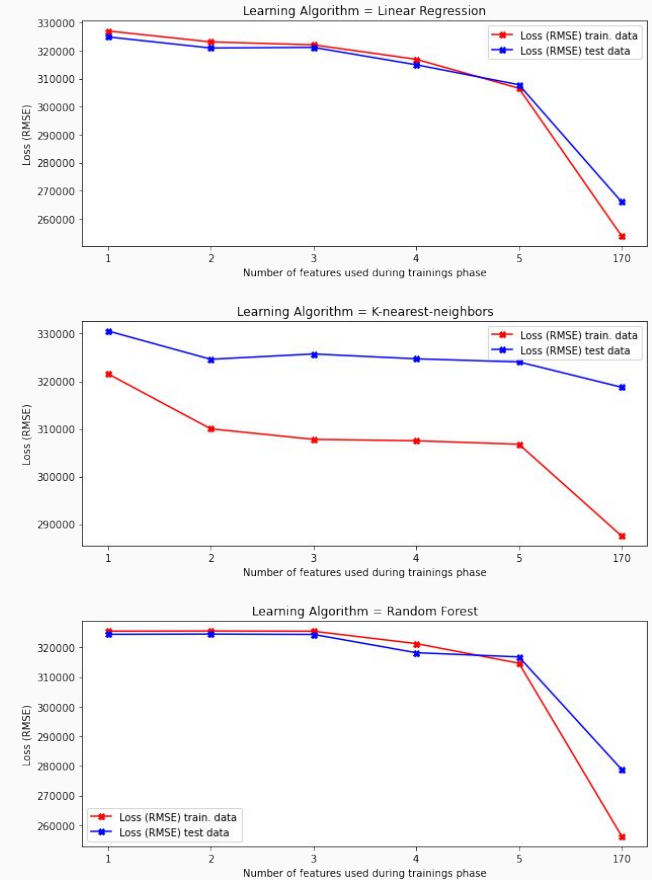
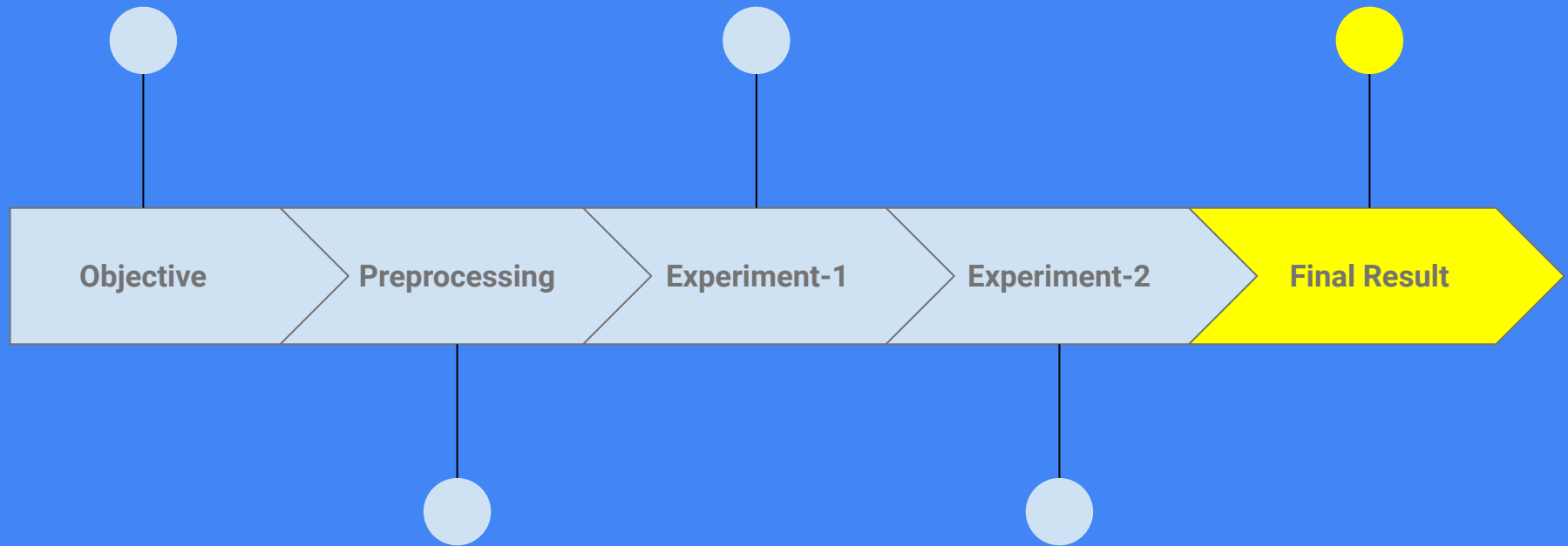


Figure 5 - Performance of Learning Algorithms



Final Result

Result: Best Model uses Multiple Lineare Regression (trained on all 170 features)

→ but: test data RMSE ~270000

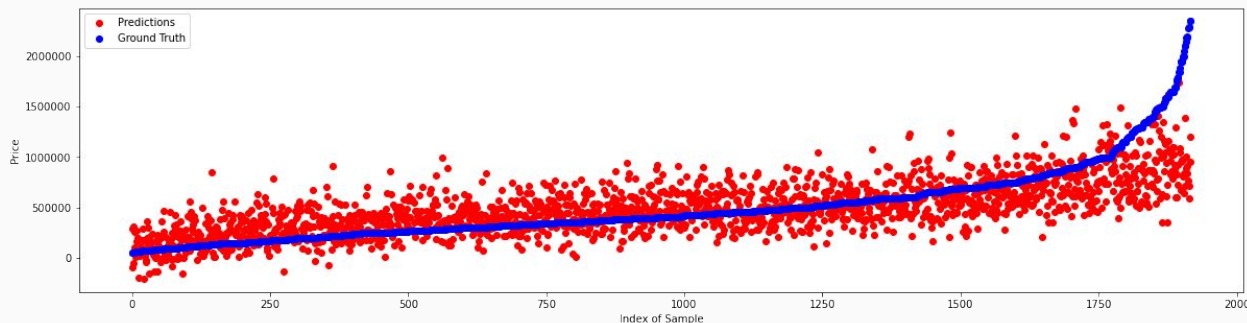


Figure 6 – Comparison between Ground Truth and Predictions

Conclusion: Even for the best model, the RMSE values are so high that it cannot make very accurate price predictions.

Thank you!

Questions?

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