

01-credit-risk-model-feature-engineering

September 22, 2025

1 Model Development with FEAST Feature Store Tutorial

1.1 Objective

This three-part series of Notebooks is to demonstrate how FEAST is integrated as the ML Feature Store during the Model Development Journey:

1. 01 - Feature Engineering
2. 02 - Feature Registration
3. 03 - Feature Consumption (Model Training)

1.2 Model

We develop a model that predicts if a credit loan customer can be a bad credit loan using the credit risk dataset.

1.3 Dataset

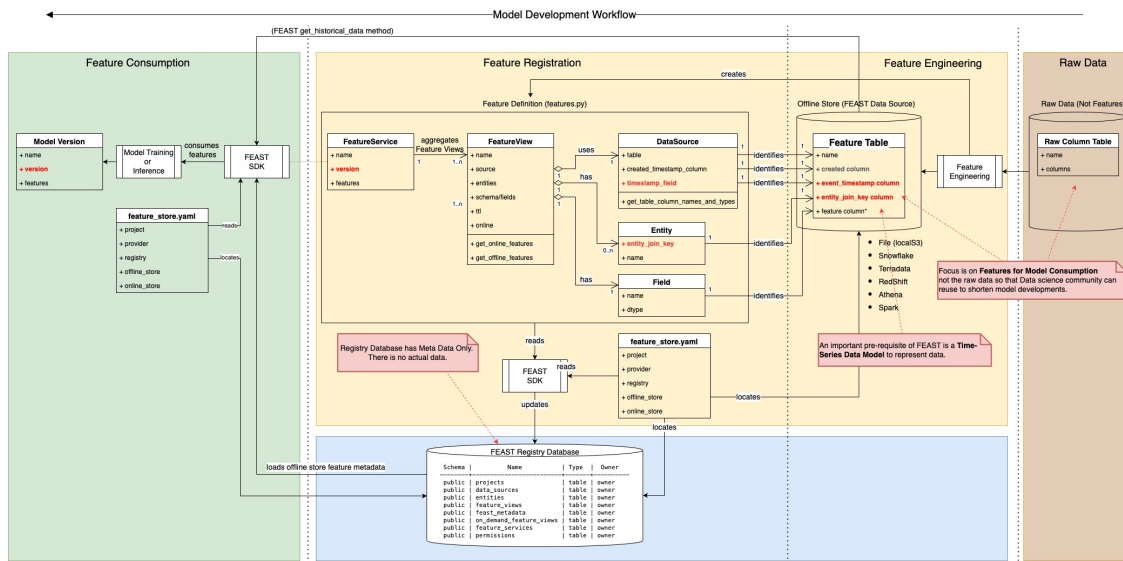
Use the trimmed [Bank Customer Credit Risk dataset](#) to have only:

Age (numeric) Sex (text: male, female) Job (numeric: 0 - unskilled and non-resident, 1 - unskilled and resident, 2 - skilled, 3 - highly skilled) Housing (text: own, rent, or free) Saving accounts (text - little, moderate, quite rich, rich) Checking account (numeric, in DM - Deutsch Mark) Credit amount (numeric, in DM) Duration (numeric, in month) Purpose(text: car, furniture/equipment, radio/TV, domestic appliances, repairs, education, business, vacation/others Risk (Value target - Good or Bad Risk)

See [german-credit-data-with-risk](#) to see the data in Kaggle.

1.4 Model Development Workflow (Right to Left)

The diagram depicts the model development flow and how FEAST is involved to provide the Feature Store functionality.



2 Local Deployment Environment

The tutorial provides the automated script to setup the environment to run the model development workflow.

3 Feature Engineering

The goal is **Features in the Offline Store** for Model Training Consumption.

3.1 This Notebook (01 Feature Engineering)

This notebook goes through the steps of:

1. Data Exploration,
2. Feature Engineering to generate the **Features to be consumed by the model training**, and,
3. Upload them to the **Offline Store**.

4 Setup

4.1 Note

Install OpenMP runtime on Macbook.

```
brew install libomp
```

5 Raw Data (Bank Customer Credit Risk)

```
<class 'pandas.core.frame.DataFrame'>
Index: 1000 entries, 0 to 999
Data columns (total 10 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Age                   1000 non-null  int64
1   Sex                   1000 non-null  object
2   Job                   1000 non-null  int64
3   Housing               1000 non-null  object
4   Saving accounts       817 non-null   object
5   Checking account      606 non-null   object
6   Credit amount         1000 non-null  int64
7   Duration              1000 non-null  int64
8   Purpose               1000 non-null  object
9   Risk                  1000 non-null  float64
dtypes: float64(1), int64(4), object(5)
memory usage: 85.9+ KB
None
```

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount
Duration				Purpose	Risk		
0	67	male	2	own	NaN	little	1169
6			radio/TV	0.0			
1	22	female	2	own	little	moderate	5951
48			radio/TV	1.0			
2	49	male	1	own	little	NaN	2096
12			education	0.0			
3	45	male	2	free	little	little	7882
42			furniture/equipment	0.0			
4	53	male	2	free	little	little	4870
24			car	1.0			

5.0.1 Column Types

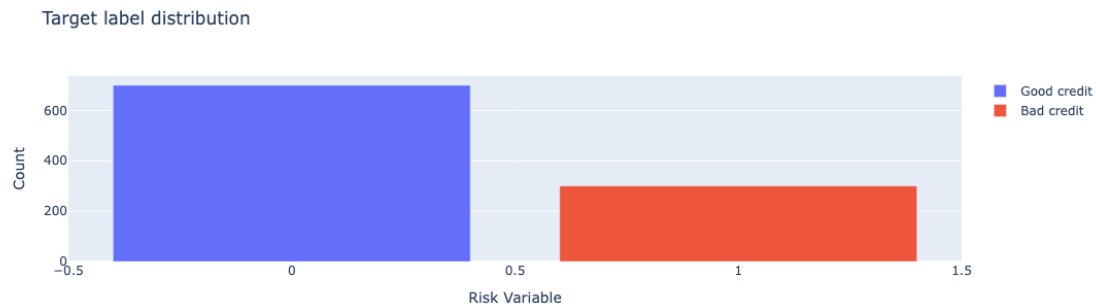
5.0.2 Unique Categorical Values

```
Sex           : [male, female]
Job           : [2, 1, 3, 0]
Housing       : [own, free, rent]
Saving accounts : [little, quite rich, rich, moderate]
Checking account : [little, moderate, rich]
Purpose       : [radio/TV, education, furniture/equipment, car, business,
domestic appliances, repairs, vacation/others]
```

6 EDA

6.1 Target label (Risk) and imbalance

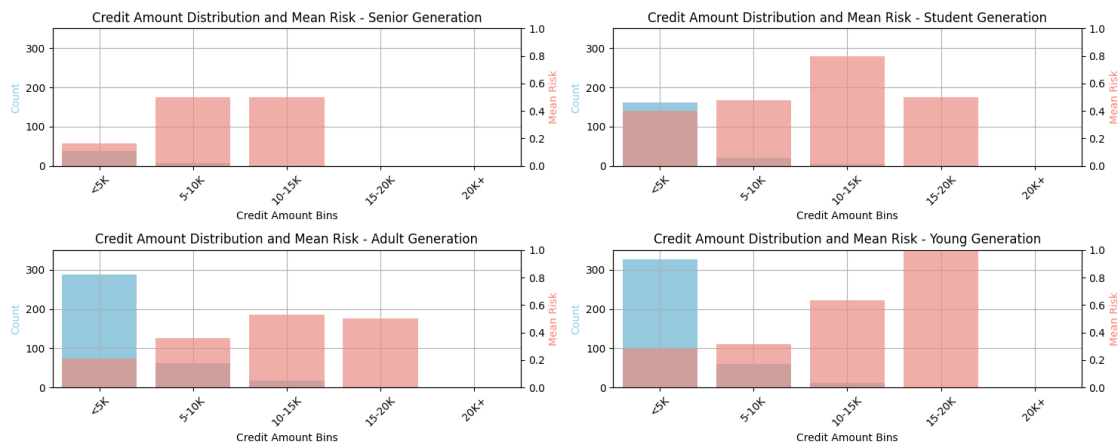
Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount
Duration	Purpose	Risk	Generation	Amount		
0	67	male	2	own	NaN	little
6	radio/TV	0.0	Senior	<5K		1169



Non Risky data is [2.33] more than Risky.

6.2 Risk by Credit Amount

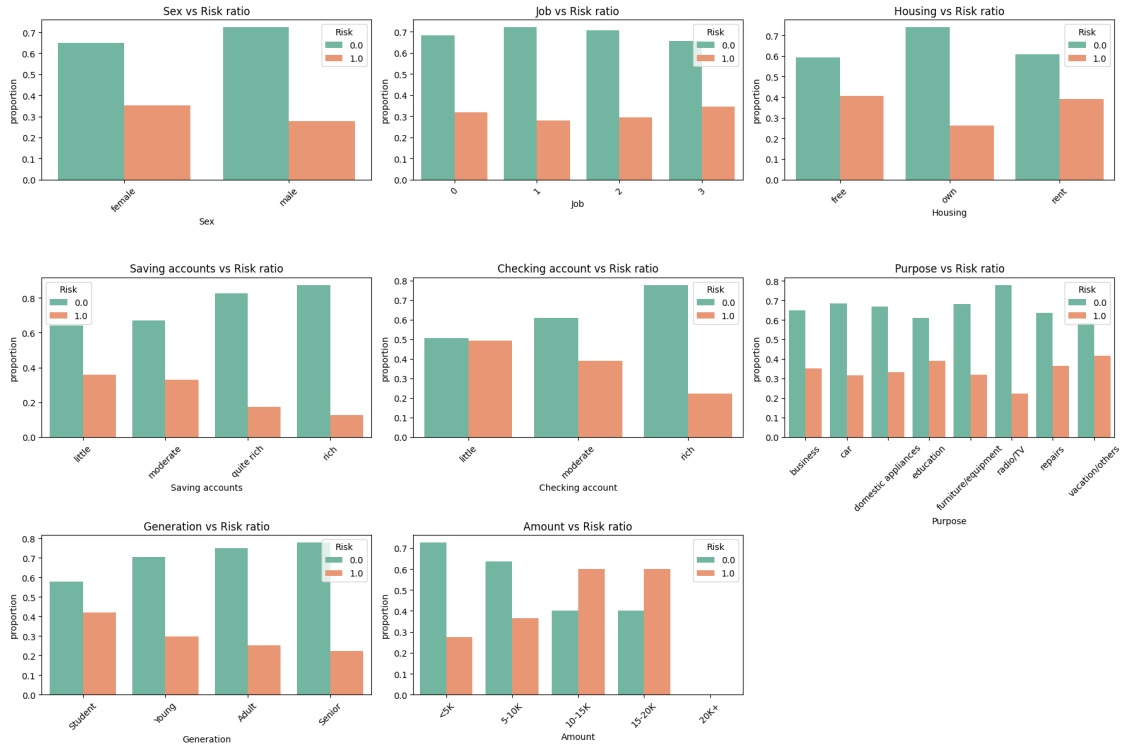
Higher the amount, higher the risk.

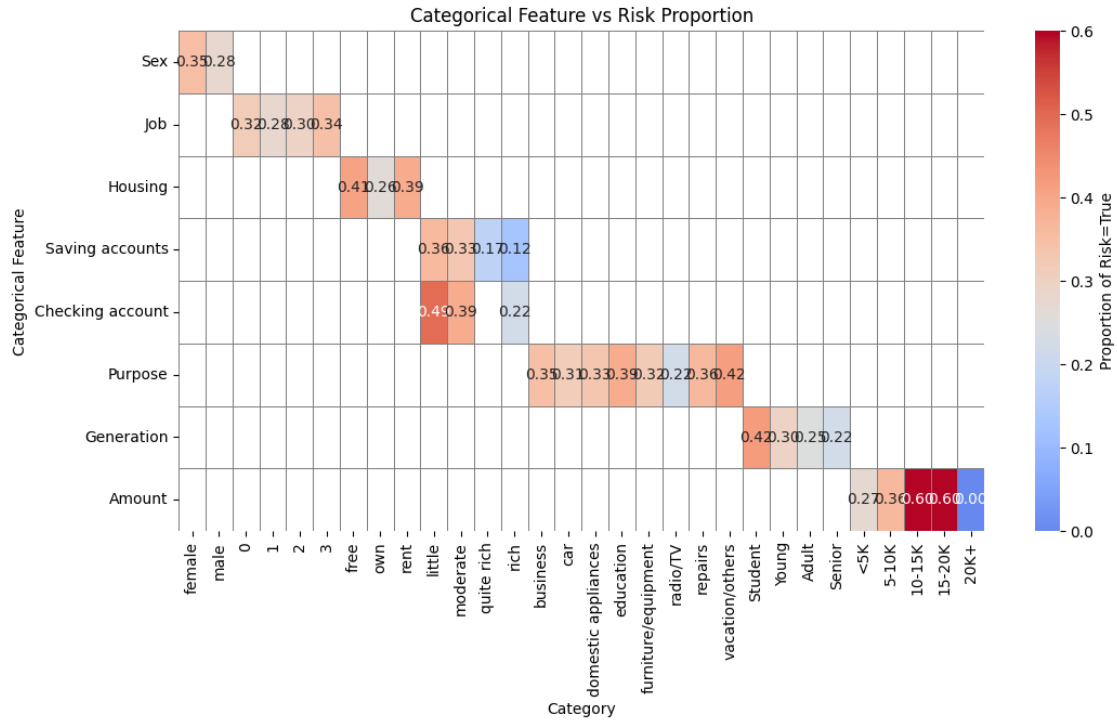


7 Risk Correlation

INFO:matplotlib.category:Using categorical units to plot a list of strings that are all parsable as floats or dates. If these strings should be plotted as

numbers, cast to the appropriate data type before plotting.
 INFO:matplotlib.category:Using categorical units to plot a list of strings that are all parsable as floats or dates. If these strings should be plotted as numbers, cast to the appropriate data type before plotting.





8 Featur Engineering

Supposing the EDA has been done and concluded:

1. Not to use `Duration` column.
2. Convert all other columns to categorical.
3. One Hot Encode all the categorical columns.

9 Features for Model Consumption

Verify the features to be consumed by the Model Training

```
<class 'pandas.core.frame.DataFrame'>
```

Index: 1000 entries, 0 to 999

Data columns (total 36 columns):

#	Column	Non-Null Count	Dtype
0	risk	1000 non-null	float64
1	gender_female	1000 non-null	float32
2	gender_male	1000 non-null	float32
3	job_0	1000 non-null	float32
4	job_1	1000 non-null	float32

5	job_2	1000	non-null	float32
6	job_3	1000	non-null	float32
7	housing_free	1000	non-null	float32
8	housing_own	1000	non-null	float32
9	housing_rent	1000	non-null	float32
10	saving_accounts_little	1000	non-null	float32
11	saving_accounts_moderate	1000	non-null	float32
12	saving_accounts_no_inf	1000	non-null	float32
13	saving_accounts_quite_rich	1000	non-null	float32
14	saving_accounts_rich	1000	non-null	float32
15	checking_account_little	1000	non-null	float32
16	checking_account_moderate	1000	non-null	float32
17	checking_account_no_inf	1000	non-null	float32
18	checking_account_rich	1000	non-null	float32
19	purpose_business	1000	non-null	float32
20	purpose_car	1000	non-null	float32
21	purpose_domestic_appliances	1000	non-null	float32
22	purpose_education	1000	non-null	float32
23	purpose_furniture_equipment	1000	non-null	float32
24	purpose_radio_tv	1000	non-null	float32
25	purpose_repairs	1000	non-null	float32
26	purpose_vacation_others	1000	non-null	float32
27	generation_student	1000	non-null	float32
28	generation_young	1000	non-null	float32
29	generation_adult	1000	non-null	float32
30	generation_senior	1000	non-null	float32
31	amount_0	1000	non-null	float32
32	amount_1	1000	non-null	float32
33	amount_2	1000	non-null	float32
34	amount_3	1000	non-null	float32
35	amount_4	1000	non-null	float32

dtypes: float32(35), float64(1)

memory usage: 152.3 KB

	risk	gender_female	gender_male	job_0	job_1	job_2	job_3	housing_free	housing_own	housing_rent	saving_accounts_little	saving_accounts_moderate	saving_accounts_no_inf	saving_accounts_quite_rich	saving_accounts_rich	checking_account_little	checking_account_moderate	checking_account_no_inf	checking_account_rich	purpose_business	purpose_car	purpose_domestic_appliances	purpose_education	purpose_furniture_equipment	purpose_radio_tv	purpose_repairs	purpose_vacation_others	generation_student	generation_young	generation_adult	generation_senior	amount_0	amount_1	amount_2	amount_3	amount_4		
0	0.0																																					
1.0																																						
1.0																																						
0.0																																						

0.0			0.0			0.0			0.0
1.0		0.0			0.0			0.0	
0.0		0.0		1.0		1.0		0.0	0.0
0.0									
1	1.0		1.0		0.0	0.0	0.0	1.0	0.0
1.0		0.0			1.0				0.0
0.0				0.0			0.0		
1.0			0.0				0.0		0.0
0.0			0.0				0.0		
1.0		0.0			0.0			1.0	
0.0		0.0		0.0		0.0		1.0	0.0
0.0									
2	0.0		0.0		1.0	0.0	1.0	0.0	0.0
1.0		0.0			1.0				0.0
0.0				0.0			0.0		
0.0			1.0				0.0		0.0
0.0			0.0				1.0		
0.0		0.0			0.0			0.0	
0.0		1.0		0.0		1.0		0.0	0.0
0.0									
0.0									

9.1 Save Features to csv

9.2 Dumpy fields for FEAST

FEAST requires time-series data structure and an entity key of each time-series record.

	risk	gender_female	gender_male	job_0	job_1	job_2	job_3	housing_free	housing_own	housing_rent	saving_accounts_little	saving_accounts_moderate	saving_accounts_no_inf	saving_accounts_quite_rich	saving_accounts_rich	checking_account_little	checking_account_moderate	checking_account_no_inf	checking_account_rich	purpose_business	purpose_car	purpose_domestic_appliances	purpose_education	purpose_furniture_equipment	purpose_radio_tv	purpose_repairs	purpose_vacation_others	generation_student	generation_young	generation_adult	generation_senior	amount_0	amount_1	amount_2	amount_3	amount_4	event_timestamp	created	entity_id								
0	0.0			0.0		0.0	1.0	0.0																																							
1.0		0.0				0.0																																									
1.0				0.0				0.0																																							
0.0				0.0				0.0																																							
0.0				0.0				0.0																																							
1.0		0.0				0.0																																									
0.0		0.0				1.0		1.0		0.0		0.0																																			
0.0	2025-09-18 12:27:23.123026	2025-09-18 12:27:23.123026																																													
1	1.0			1.0		0.0		0.0		0.0		1.0		0.0																																	
1.0		0.0				1.0																																									
0.0				0.0				0.0																																							

1.0		0.0		0.0		0.0		0.0
0.0			0.0		0.0			0.0
1.0		0.0		0.0		1.0		
0.0		0.0		0.0		1.0	0.0	0.0
0.0	2025-09-18 12:27:23.123026	2025-09-18 12:27:23.123026					2	
2	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0
1.0		0.0		1.0			0.0	
0.0			0.0		0.0			0.0
0.0		1.0			0.0		0.0	
0.0			0.0		1.0			0.0
0.0		0.0		0.0		0.0		
0.0		1.0		0.0	1.0	0.0	0.0	0.0
0.0	2025-09-18 12:27:23.123026	2025-09-18 12:27:23.123026					3	
3	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0
0.0		0.0		1.0			0.0	
0.0			0.0		0.0			1.0
0.0		0.0			0.0		0.0	
0.0			0.0		0.0			1.0
0.0		0.0		0.0		0.0		
0.0		1.0		0.0	0.0	1.0	0.0	0.0
0.0	2025-09-18 12:27:23.123026	2025-09-18 12:27:23.123026					4	
4	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0
0.0		0.0		1.0			0.0	
0.0			0.0		0.0			1.0
0.0		0.0			0.0		0.0	
1.0			0.0		0.0			0.0
0.0		0.0		0.0		0.0		
0.0		1.0		0.0	1.0	0.0	0.0	0.0
0.0	2025-09-18 12:27:23.123026	2025-09-18 12:27:23.123026					5	

10 Features to Offline Store

10.1 Offline Store Paramters

```
INFO:root:Successfully loaded YAML:
../deployment/feast/feature_repository/feature_store.yaml
```

```
{'host': 'localhost',
 'port': 5432,
 'database': 'offline_features',
 'user': 'dbadm',
 'schema': 'credit',
 'table_name': 'customer_credit_risk_offline_features'}
```

10.2 Insert into offline store table

```
INFO:root:Table 'credit.customer_credit_risk_offline_features' does not exist
INFO:root:Available tables: []
Engine auto-disposed
INFO:root:Inserting [1000] rows in [1] batches...
Inserting batches: 100%|

| 1/1 [00:00<00:00, 2.09it/s]

Successfully inserted all 1000 rows!
Engine auto-disposed
```

10.3 Verify

```
Engine auto-disposed

risk
gender_female
gender_male
job_0
job_1
job_2
job_3
housing_free
housing_own
housing_rent
saving_accounts_little
saving_accounts_moderate
saving_accounts_no_inf
saving_accounts_quite_rich
saving_accounts_rich
checking_account_little
checking_account_moderate
checking_account_no_inf
checking_account_rich
purpose_business
purpose_car
purpose_domestic_appliances
purpose_education
purpose_furniture_equipment
purpose_radio_tv
purpose_repairs
purpose_vacation_others
generation_student
generation_young
generation_adult
```

generation_senior
 amount_0
 amount_1
 amount_2
 amount_3
 amount_4
 event_timestamp
 created
 entity_id

	risk	gender_female	gender_male	job_0	job_1	job_2	job_3	housing_free	housing_own	housing_rent	saving_accounts_little	saving_accounts_moderate	saving_accounts_no_inf	saving_accounts_quite_rich	saving_accounts_rich	checking_account_little	checking_account_moderate	checking_account_no_inf	checking_account_rich	purpose_business	purpose_car	purpose_domestic_appliances	purpose_education	purpose_furniture_equipment	purpose_radio_tv	purpose_repairs	purpose_vacation_others	generation_student	generation_young	generation_adult	generation_senior	amount_0	amount_1	amount_2	amount_3	amount_4	event_timestamp	created	entity_id					
0	0.0										0.0			1.0	0.0	0.0	1.0	0.0																										
1.0			0.0											0.0				0.0																										
1.0											0.0								0.0																									
0.0											0.0																																	
0.0														0.0																														
1.0											0.0																																	
0.0											0.0																																	
0.0	2025-09-18	12:27:23.123026	2025-09-18	12:27:23.123026																																								