



# LOAN RISK DATA PIPELINE (BRONZE → SILVER → GOLD)

CS611 Assignment 1: Data Processing Pipelines

Yip Pak Kei (01507599)

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# WHY BUILD THIS PIPELINE?

## Business Problem

- The bank issues cash loans.
- Need to predict loan default risk at the point of application.
- Why?
  - Reduce credit losses.
  - Support responsible lending.
  - Improve regulatory compliance.

## Technical Objective

- Build a structured, reproducible and auditable data pipeline following medallion architecture.
- Outputs:
  - Feature Store (Gold): model-ready features.
  - Label Store (Gold): default labels
- Ensure:
  - Clean, consistent data
  - Scalable for future loan risk ML models
  - Traceable from raw to Model.

# ARCHITECTURE OVERVIEW



# RAW DATA TO BRONZE

## Attributes



Clickstream



Financials



Loans



## Raw Data

Various data sources:

- Clickstream - User's historical usage behavior on our bank's app.
- Attributes - User's profile.
- Financials - Users' financials profile.
- Loans - Loan records (target label table).



ETL

- **Extract:** Loans, Clickstream, Financials
- **Transform:** Keep minimal and just filtering by snapshot date.
- **Load:** Stored as partitioned CSVs by snapshot dates in individual data store.



## Design Decisions

- Keep data untouched for audit trail.
- Partition by snapshot month for reproducibility.
- No schema enforcement on plaintext csv file.



Bronze



Jan

Feb

Mar

Dec

Attributes



Financials



Clickstream



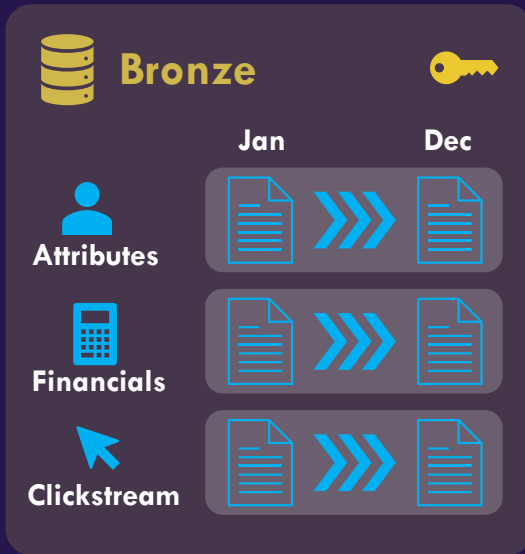
Loans



## Confidentiality

- The Bronze datamart is classified as "Confidential" since Personal Identifiable Information (PII) information such as Name and SSN are stored in it.

# BRONZE TO SILVER (USERS)



## Exploratory Data Analysis

- Some numerical fields contain invalid string characters.
- Certain numerical values fall outside reasonable ranges.
- Credit History Age and Payment Behavior are stored in natural language format.

## Key Insights for ETL

- Strip non-numeric characters from numerical fields.
- Remove values that are logically impossible while retaining valid extremes.
- Transform natural language fields into structured, machine-readable formats.



## ETL

- Extract:** Bronze clickstream, attributes and financials.
- Transform:**
  - Enforce schema on all features.
  - Attributes:** Mask PII, validate and bin Age range.
  - Clickstream:** Convert 20 features (fe\_1 to fe\_20) to integers.
  - Financials:** Parse numeric fields, cleans invalids, standardize "Type\_of\_Loan" and "Credit\_History\_Age" and split payment behaviour.
- Load:** Stored as cleaned, standardized and partitioned Parquet files by snapshot dates.



## Design Decisions

- The PII are masked in the Silver layer to ensure sensitive information would not be accidentally shared within the enterprise.
- Schema enforcement prevents dirty data from propagating.
- Separate logic per data domain ensures data quality early.
- Partition by snapshot month for reproducibility.

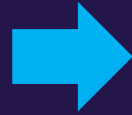


## Silver Layer

- "Enterprise view" of all business entities.
- "just-enough" transformations and data cleansing of the data from the Bronze layer.
- Data schema enforcement.



# BRONZE TO SILVER(LOANS)



## ETL

- **Extract:** Load Bronze loans data.
- **Transform:**
  - Enforce schema on all loans features.
  - Add derived fields:
    - MOB = Month on Book.
    - DPD = Days Past Due (30 days).
    - Installments Missed (Derive DPD)
    - First Missed Day (Derive DPD)
- **Load:** Stored as **cleaned, standardized** and **partitioned Parquet** files by snapshot dates.



## Silver



## Design Decisions

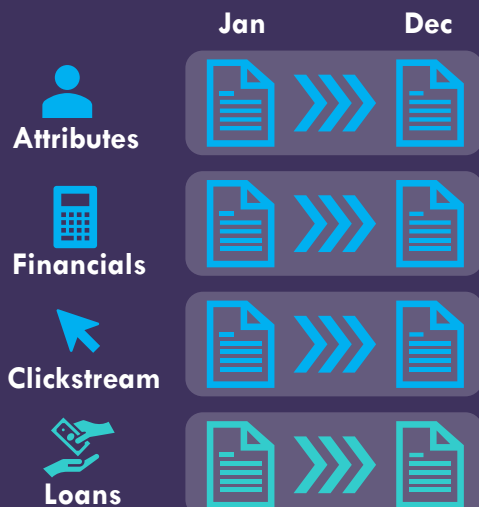
- Schema enforcement prevents dirty data from propagating.
- Derive **additional fields** for next stage exploratory data analysis to determinate the target label in Gold layer.
- Partition by snapshot month for **reproducibility** **auditability**.

## Silver Layer

- "Enterprise view" of all business entities.
- "just-enough" transformations and data cleansing of the data from the Bronze layer.
- Data schema enforcement.

# SILVER TO GOLD (FEATURES)

## Silver



### Exploratory Data Analysis

- Some clickstream snapshot dates fall within the 6-month observation window.
- A single user may have multiple clickstream records with different snapshot dates.

### Key Insights for ETL

- Records within the 6-month observation window must be excluded to avoid data leakage.
- Clickstream records should be aggregated at the user-level.

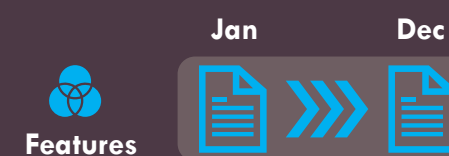
## ETL

- Extract:** Silver clickstream, attributes, financials and loans data.
- Transform:**
  - For each loan, include only clickstream, attributes, and financial records up to 5 months before the 6-month observation point (MOB=6).
  - Attributes:** Retain Age bin and Occupation only.
  - Clickstream:** Aggregate means of all behavioral features.
  - Financials:** Retain all standardized features from the Silver layer.
  - Feature Engineering:**
    - Create **ratios** (e.g., EMI-to-income ratio).
    - Generate **risk flags**, etc.
    - Encodings categorical features.
  - Merge clickstream, attributes, and financials into a consolidated feature table.
- Load:** Stored as partitioned Parquet files by label snapshot dates in Gold feature store.

### Design Decisions

- PII is not essential for the ML training. In addition, Customer ID is sufficient as an identifier.
- Generalize** the user clickstream behavioral patterns by aggregating the mean of historical interactions.
- Prevent the peeking into the future** by filtering out any predictor features before the observation window used to compute the label.
- Aggregate** all crucial user profile, financials and behavioral features into a new feature table ready for the ML training.

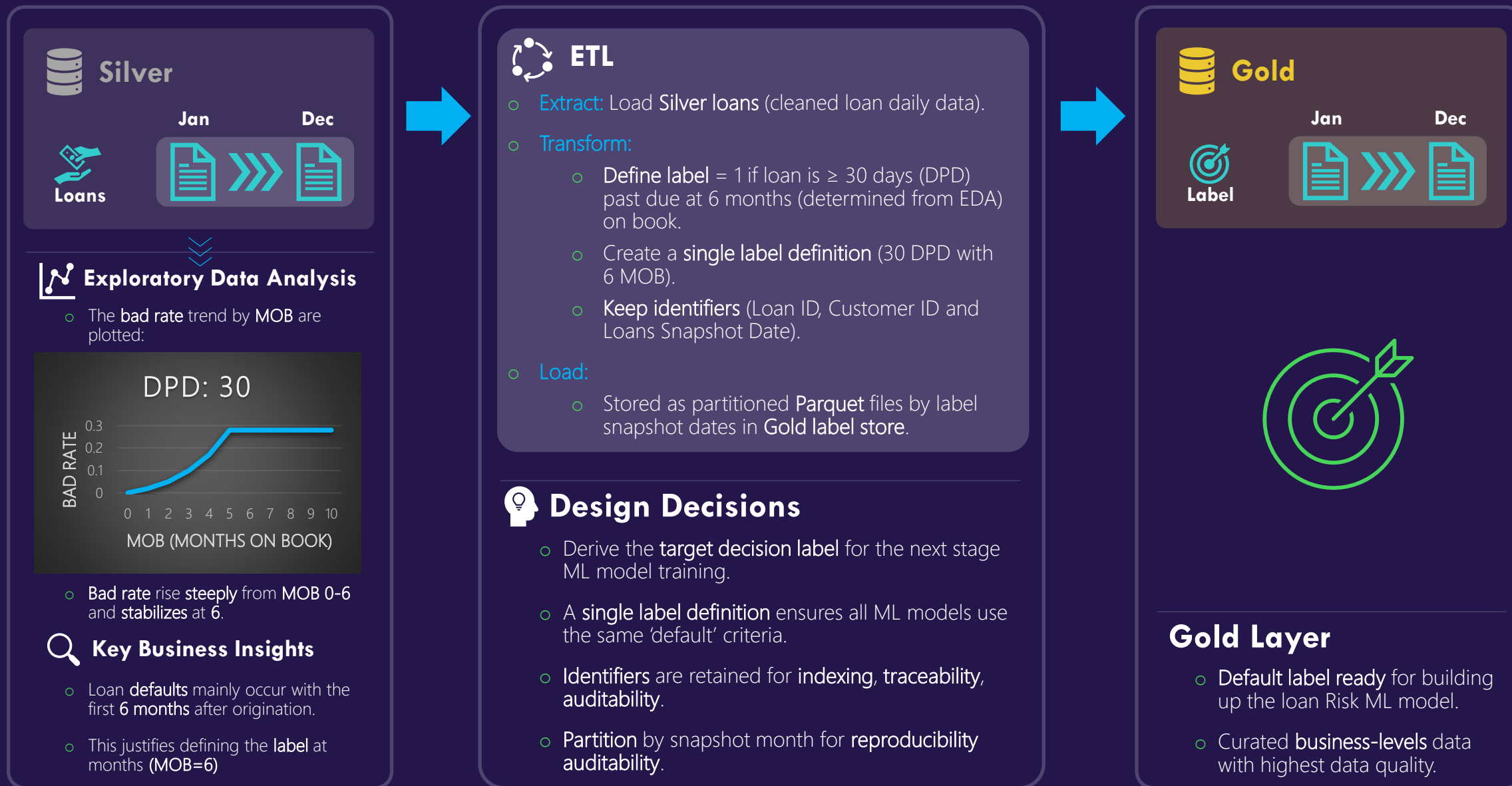
## Gold



### Gold Layer

- Model-ready features** for building up the loan Risk ML model.
- Curated **business-levels** data with highest data quality.

# SILVER TO GOLD (LABEL)





# NEXT STEPS



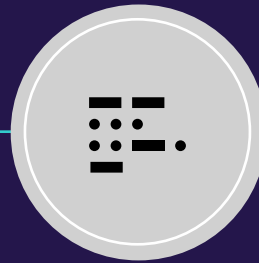
## Step 1 ●

Split Gold data into train, validation, test, and Out-of-Time (OOT) sets to ensure temporal generalization.



## Step 2 ●

Select ML models based on available Gold data. (e.g. Logistic Regression, Random Forest, XGBoost).



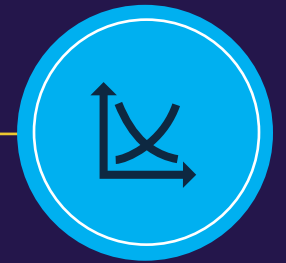
## Step 3 ●

One-hot encoding for categorical variables (Occupation, Loan Type).



## Step 4 ●

Normalize and scale numeric features (e.g., income, EMI).



## Goal ●

Train and evaluate loan risk ML models; choose the best based on metrics. (e.g. AUC, F1, recall).

# APPENDIX – DATA TABLES

Bronze Stores		Columns	
bronze_users_attributes	<ul style="list-style-type: none"><li>Customer_ID,</li><li>Name,</li><li>Age,</li><li>SSN,</li><li>Occupation,</li><li>snapshot_date</li></ul>		
bronze_users_financials	<ul style="list-style-type: none"><li>Customer_ID,</li><li>Annual_Income,</li><li>Monthly_Inhand_Salary,</li><li>Num_Bank_Accounts,</li><li>Num_Credit_Card,</li><li>Interest_Rate,</li><li>Num_of_Loan,</li><li>Type_of_Loan,</li><li>Delay_from_due_date,</li><li>Num_of_Delayed_Payment,</li><li>Changed_Credit_Limit,</li><li>Num_Credit_Inquiries,</li><li>Credit_Mix,</li><li>Outstanding_Debt,</li><li>Credit_Utilization_Ratio,</li><li>Credit_History_Age,</li><li>Payment_of_Min_Amount,</li><li>Total_EMI_per_month,</li><li>Amount_invested_monthly,</li><li>Monthly_Balance,</li><li>Payment_Behaviour,</li><li>snapshot_date</li></ul>		
bronze_users_clickstream	<ul style="list-style-type: none"><li>Customer_ID, fe_1 ... fe_20,</li><li>snapshot_date</li></ul>		
bronze_loan_daily	<ul style="list-style-type: none"><li>loan_id,</li><li>Customer_ID,</li><li>loan_start_date,</li><li>tenure,</li><li>installment_num,</li><li>loan_amt,</li><li>due_amt,</li><li>paid_amt,</li><li>overdue_amt,</li><li>balance,</li><li>snapshot_date</li></ul>		
Silver Stores		Columns	
silver_users_attributes	<ul style="list-style-type: none"><li>Customer_ID,</li><li>Name</li><li>Masked,</li><li>Age,</li><li>SSN_Masked,</li><li>Occupation,</li><li>snapshot_date</li></ul>		
silver_users_financials	<ul style="list-style-type: none"><li>Customer_ID,</li><li>Annual_Income,</li><li>Monthly_Inhand_Salary,</li><li>Num_Bank_Accounts,</li><li>Num_Credit_Card,</li><li>Interest_Rate,</li><li>Num_of_Loan,</li><li>Type_of_Loan (standardized),</li><li>Delay_from_due_date,</li><li>Num_of_Delayed_Payment,</li><li>Changed_Credit_Limit,</li><li>Num_Credit_Inquiries,</li><li>Credit_Mix (normalized),</li><li>Outstanding_Debt,</li><li>Credit_Utilization_Ratio,</li><li>Credit_History_Age (months),</li><li>Payment_of_Min_Amount,</li><li>Total_EMI_per_month,</li><li>Amount_invested_monthly,</li><li>Monthly_Balance,</li><li>Payment_Behaviour_Spent,</li><li>Payment_Behaviour_Payment,</li><li>snapshot_date</li></ul>		
silver_users_clickstream	<ul style="list-style-type: none"><li>Customer_ID,</li><li>fe_1 ... fe_20 as integers,</li><li>snapshot_date</li></ul>		
silver_loan_daily	<ul style="list-style-type: none"><li>Bronze columns +</li><li>Derived columns:</li><li>mob,</li><li>dpd,</li><li>installments_missed,</li><li>first_missed_date</li></ul>		
Gold Stores		Columns	
gold_feature_store	<ul style="list-style-type: none"><li>Metadata:<ul style="list-style-type: none"><li>Customer_ID,</li><li>label_snapshot_date,</li><li>attributes_snapshot_date,</li><li>financials_snapshot_date</li></ul></li><li>Attributes:<ul style="list-style-type: none"><li>Age_bin,</li><li>Occupation</li></ul></li><li>Financials:<ul style="list-style-type: none"><li>Annual_Income,</li><li>Monthly_Inhand_Salary,</li><li>Num_Bank_Accounts,</li><li>Num_Credit_Card,</li><li>Num_of_Loan,</li><li>Type_of_Loan,</li><li>Interest_Rate,</li><li>Delay_from_due_date,</li><li>Num_of_Delayed_Payment,</li><li>Num_Credit_Inquiries,</li><li>Outstanding_Debt,</li><li>Credit_Utilization_Ratio,</li><li>Credit_History_Age,</li><li>Total_EMI_per_month,</li><li>Amount_invested_monthly,</li><li>Monthly_Balance</li></ul></li><li>Encodings:<ul style="list-style-type: none"><li>Credit_Mix_Enc,</li><li>Payment_of_Min_Amount_Enc,</li><li>Payment_Behaviour_Spent_Enc,</li><li>Payment_Behaviour_Payment_Enc</li></ul></li><li>Engineered ratios:<ul style="list-style-type: none"><li>emi_to_income_ratio,</li><li>debt_to_income_ratio,</li><li>avg_delay,</li><li>balance_to_income_ratio</li></ul></li><li>Flags:<ul style="list-style-type: none"><li>high_credit_inquiry_flag,</li><li>high_utilization_flag,</li><li>high_emi_burden_flag,</li><li>negative_balance_flag</li></ul></li><li>Clickstream features:<ul style="list-style-type: none"><li>fe_1_mean ... fe_20_mean</li></ul></li></ul>		
gold_label_store	<ul style="list-style-type: none"><li>loan_id,</li><li>Customer_ID,</li><li>label,</li><li>label_def,</li><li>snapshot_date</li></ul>		