Lecture 1

Interpretable Machine Learning for Finance

Instructor

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- Financial Risk Manager (FRM) Certified since 2012
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- Senior Credit Risk Analyst at a credit bureau (2013-2014)
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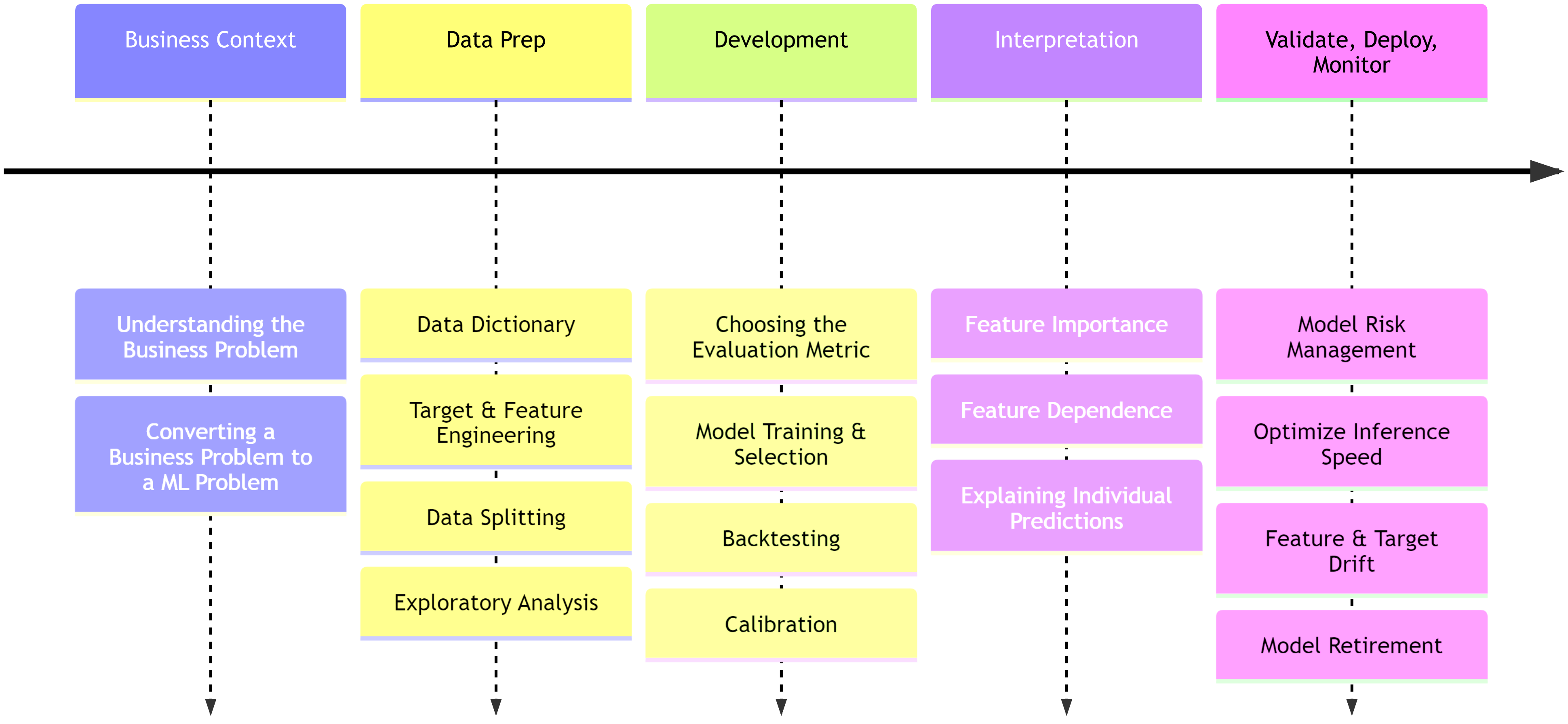
Model Lifecycle



Business Context

1. Acquire new clients with a marketing response model (aka prescreen model)
2. Approve (or reject) loan applications with a credit scorecard model
3. Explain rejected loan applications with counterfactuals
4. Estimate lifetime credit losses with a transition matrix model
5. Detect fraud with a cost-sensitive model

Data Sets

1. Borrower data from an Indian Bank and Credit Bureau. The instructor modified the data to include `campaign_id`, `control_group`, and `response_flag`. (Azad 2024).
2. Loan Performance data from LendingClub. Includes both accepted and rejected loan applications. (George 2019)
3. Single-Family Loan Performance data from Fannie Mae. (Fannie Mae 2024)
4. Simulated data from the *Fraud Detection Handbook* . (Le Borgne et al. 2022)

Model Development Tools

- AutoGluon is an open-source AutoML framework designed to automate model training and ensembling.
- AutoGluon achieves strong performance by using ensembling techniques and a comprehensive library of preset hyperparameters for each base learner.
- AutoGluon offers data preprocessing like automatic encoding of categorical variables and automatic removal of features with no variance.
- Scikit-learn provides calibration methods (e.g., Platt scaling, isotonic regression) to improve the reliability of predicted probabilities.

Interpretable ML Tools

- Rank features from most to least important
  - Permutation importance
  - SHAP importance
  - Dealing with multicollinear features
- Describe the dependence between features and predictions
  - Partial dependence plots (PDP)
  - Accumulated local effects (ALE) plots
  - SHAP dependence plots

(More) Interpretable ML tools

- Explain individual predictions
  - SHAP values
  - Counterfactuals

Prerequisites

- Comfort using supervised learning methods:
  - Generalized Linear Models
  - Trees with bagging and/or boosting
  - Cross Validation and Bias-Variance Tradeoff
- Familiarity with Python and data science libraries (i.e., pandas and scikit-learn)
- Practice with SQL databases

Assignments and Grading

1. Problem Sets (70%)
    - Weekly conceptual questions and programming exercises based on each week's topics.
    - Reinforce understanding of weekly material and practical application of concepts.
2. Kaggle Competition (30%)
    - Develop a scorecard model for loan underwriting.
    - Apply modeling techniques in a competitive scenario.
    - Students will be given a labeled training set and an unlabeled test set.
    - Students will be asked why the model rejected a loan application.
    - Grades will depend on model performance in an unlabeled test set and the quality of the explanation.

Introduction to Retail Banking

What is a Retail Bank?

Revenue Sources

- Interest collected from loans (e.g., credit cards, auto loans, personal loans, mortgages)
- Transaction fees, commissions, and service charges
- Major contributor to profitability: spread between interest collected from loans and interest paid to depositors

Expense Sources

- Employee compensation
- Interest paid to depositors
- Provision for loan losses

How could a Bank fail?

- Insufficient liquidity (not enough cash to meet obligations)
- Insufficient capital (not enough equity to absorb losses)
- High levels of non-performing loans or significant credit losses
- Sudden loss of depositor confidence leading to a bank run
- Poor risk management and poor investment decisions

What is FDIC insurance?

- Protects depositors by guaranteeing their funds up to a certain limit if a bank fails
- Aims to maintain public confidence and prevent bank runs
- Standard insurance amount in the US: $250,000 per depositor, per insured bank

How do Banks use machine learning?

- Improve the effectiveness of marketing campaigns
- Measure the credit risk of loan applicants
- Estimate the lifetime credit losses of a loan portfolio
- Detect fraudulent activities

Introduction to Credit Bureaus

US Credit Bureaus

- The US has three major credit bureaus:
  - Experian
  - TransUnion
  - Equifax
- Credit bureaus serve three major functions:
  - Collect and maintain consumer credit information
  - Provide credit reports to lenders
  - Generate credit scores

Credit Score Range: 300 to 850

- Excellent: 800+
- Very Good: 740-799
- Good: 670-739
- Fair: 580-669
- Poor: Below 580

Bureau Data

- **Borrowers**: Consumer identification, address, birthdate, employment information, and credit scores
- **Trades**: Lending accounts associated with the borrower; details include creditor name, account type, credit limit, outstanding balance, credit utilization rate, and account status
- **Trade History**: Monthly payment history for each account including payment status, balance changes, and delinquency information

(More) Bureau Data

- **Inquiries**: Records of lenders that requested the borrower’s credit report
  - Hard inquiries: affect credit score
  - Soft inquiries: do not affect credit score

Prescreen Campaigns to Acquire New Clients

Business Problem

- Identify consumers likely to respond to pre-approved credit offers
- Target prospects based on bureau attributes including recent inquiries, credit scores, and credit history
- Maximize campaign response rates while adhering to risk policy, legal, and budget constraints

Prescreening Compliance Framework

- Fair Credit Reporting Act (FCRA)
  - Verify permissible purpose and consumer opt-out status prior to prescreening
  - Ensure firm offers match the criteria used during prescreening
  - Include clear opt-out notices and instructions in every prescreened offer
  - If declined after prescreening, provide an Adverse Action Notice
- Equal Credit Opportunity Act (ECOA)
  - Prohibits discrimination based on race, color, religion, national origin, sex, marital status, or age
  - Apply consistent underwriting standards to all applicants
  - Maintain documentation to demonstrate non-discriminatory practices and facilitate regulatory reviews

Business Solution

- Develop selection criteria for credit bureau prescreening
- Combine bureau data with internal customer data if available
- Selection criteria typically includes: credit scores, geographic location, bureau attributes, estimated income, existing relationship data, and prior campaign responses

Machine Learning Problem

- Requires historical campaign data, response flags, and relevant borrower attributes
- Predict which prospects are most likely to accept the offer
- Develop a model that maximizes AUC and estimate a probability threshold that maximizes the F1 score

Machine Learning Solution

- Train a classification model on labeled data to identify strong responders
- Incorporate performance metrics such as AUC, F1 score, lift chart, and gains chart to gauge effectiveness
- Score new prospects, select high-scoring individuals for the campaign, and measure the lift and gains chart over a control group

Citations

Azad, Rohan. 2024. "Leading Indian Bank & CIBIL Real-World Dataset." https://www.kaggle.com/datasets/saurabhbadole/leading-indian-bank-and-cibil-real-world-dataset/data.

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George, Nate. 2019. "All Lending Club Loan Data." https://www.kaggle.com/datasets/wordsforthewise/lending-club.

Le Borgne, Yann-Aël, Wissam Siblini, Bertrand Lebichot, and Gianluca Bontempi. 2022. *Reproducible Machine Learning for Credit Card Fraud Detection - Practical Handbook*. Université Libre de Bruxelles. https://github.com/Fraud-Detection-Handbook/fraud-detection-handbook.