Fraud detection in credit card transaction

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1. Problem

1.1 Business Problem

Fraud detection is a problem that applies in many industries including banks, financial industries, insurance, government agencies and law enforcement. On the other hand, its becoming billion-dollar business (2018 PWC), and it is increasing every year as well as companies are facing huge losses.

1.2 Technical Problem

Detecting fraud transaction is becoming more chalanging every day, the people who commit fraud are becoming starter

Information technology, data science, business reengineering are identifying or trying to eliminate control but in mean time, information systems may present more new ways to commit fraud.

Some common Frauds:

- Credit Card Fraud
- Tax Fraud
- Fraud in Supply Chains, Retail networks, Purchase Department
- Fraud in Insurances
- Fraud in Healthcare

Traditional programming techniques

- Frequency between unsuccessful tries
- Registered customer's location like country, postcode or address
- 3D code in credit card payment
- other unusual behaviour that captured by human

Machine Learning techniques in Fraud Detection

One of the common technique to detect fraud in credit card payment is Anomaly Detection that used to identify unusual patterns that do not conform to expected behavior, called outliers.

Other common usages of Anomaly Detection:

- Manufactoring
- Data Center
- Airplane engine
- Website

Some commong Machine Learning-based approaches for Anomaly Detection

- Density-Based Anomaly Detection (example: k-NN, LOF)
- Clustering-Based Anomaly Detection
- Support Vector Machine-Based Anomaly Detection
- Isolation Forest Anomaly Detection Algorithm

Outlier vs Anamoly

Outlier: a value that you predictably find in your data that indicates your model does not work properly

Anomaly: a value that against all odds you find in your data that indicates your model does work properly

Dataset

https://www.kaggle.com/mlg-ulb/creditcardfraud

Dataset is transformed Principal Component Analysis (PCA) which is commonly used:

- Dimensionality reduction algorithm
- Speed-up Machine Learning algorithms

Observation

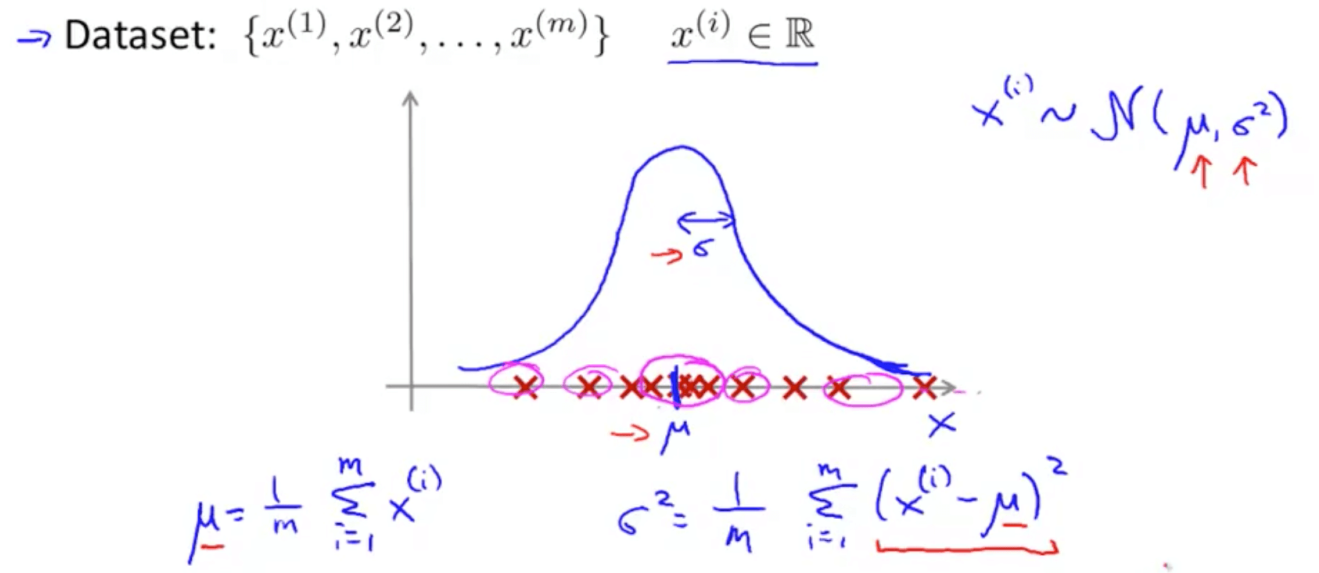
- some features (V1, V2, V3, ... ,V28) transformed to PCA and Time, Amount features not transformed.
- target is Class (1-Fraud, 0-NonFraud)

Modeling in Anomaly Detection

- ***Anomaly Detection using Gaussian Distribution***
  One of the main purposes of working on Capstone project is learning. So, personally, I am interested in Anomaly Detection technique taught by ***Andrew Ng***. It is simple, and easy to understand what

Anomaly Detection is, and I am hoping that it will be my base knowledge to understand other ML algorithms to detect Anomaly. if you were interested in this course, please click here

For example:



Source: https://www.ritchieng.com/machine-learning-anomaly-detection/

- Isolation Forest

Other good Anomaly Detection algorithms

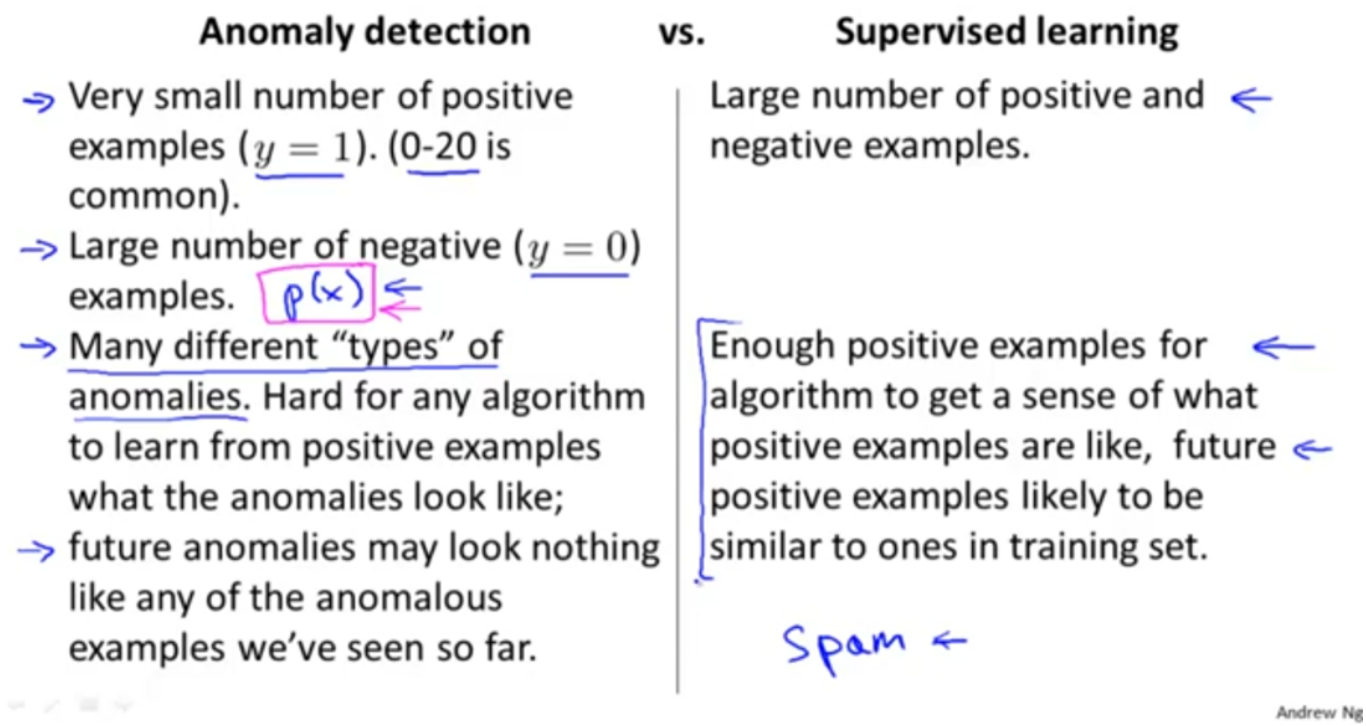
- SVM
- Clustering

Anomaly Detection vs Supervised Learning

Based on this initial EDA, this dataset does not have any null values and highly imbalance. According to Andrew NG, Anomaly Detection is best for umbalance dataset and supervised learning is better if dataset balanced. See the picture below

99.8273% of total transaction is Non Fraud

0.1727% of total transaction is Fraud



Reference

https://www.researchgate.net/publication/40227011_Credit_card_fraud_and_detection_techniques_A_review

Capstone Project Organization

```
├── LICENSE
├── Makefile           <- Makefile with commands like `make data` or `make train`
├── README.md          <- The top-level README for developers using this project.
├── data
│   ├── external       <- Data from third party sources.
│   ├── interim        <- Intermediate data that has been transformed.
│   ├── processed      <- The final, canonical data sets for modeling.
│   └── raw            <- The original, immutable data dump.
├── data-mini          <- A dataset that minimised from original dataset to run
notebook on github
├── docs               <- A default Sphinx project; see sphinx-doc.org for details
│
├── models             <- Trained and serialized models, model predictions, or
model summaries
│
├── notebooks          <- Jupyter notebooks. Naming convention is a number (for
ordering),
│                         the creator's initials, and a short `-` delimited
description, e.g.
│                         `1.0-jqp-initial-data-exploration`.
│
├── references         <- Data dictionaries, manuals, and all other explanatory
materials.
│
```

```
├── reports            <- Generated analysis as HTML, PDF, LaTeX, etc.
│   └── figures        <- Generated graphics and figures to be used in reporting
│
├── requirements.txt   <- The requirements file for reproducing the analysis
environment, e.g.
│                         generated with `pip freeze > requirements.txt`
│
├── setup.py           <- makes project pip installable (pip install -e .) so src
can be imported
├── src                <- Source code for use in this project.
│   ├── __init__.py    <- Makes src a Python module
│   │
│   ├── data           <- Scripts to download or generate data
│   │   └── make_dataset.py
│   │
│   ├── features       <- Scripts to turn raw data into features for modeling
│   │   └── build_features.py
│   │
│   ├── models         <- Scripts to train models and then use trained models to
make
│   │   │                 predictions
│   │   ├── predict_model.py
│   │   └── train_model.py
│   │
│   └── visualization  <- Scripts to create exploratory and results oriented
visualizations
│       └── visualize.py
│
└── tox.ini            <- tox file with settings for running tox; see
tox.testrun.org
```

Project based on the cookiecutter data science project template. #cookiecutterdatascience