Anomaly and fraud detection with Machine Learning

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Plan

- Anomaly/Fraud detection with machine learning/Deep learning
- Outlier detection general applications
- Applications to financial sector (banking, insurance): Towards Fintech
- Supervised vs. Unsupervised
- Algorithms and methods
- Conclusions Ensemble method (Isolation forest) and Density method (DBSCAN/HDBSCAN)

Anomaly/Fraud detection with machine learning/Deep learning

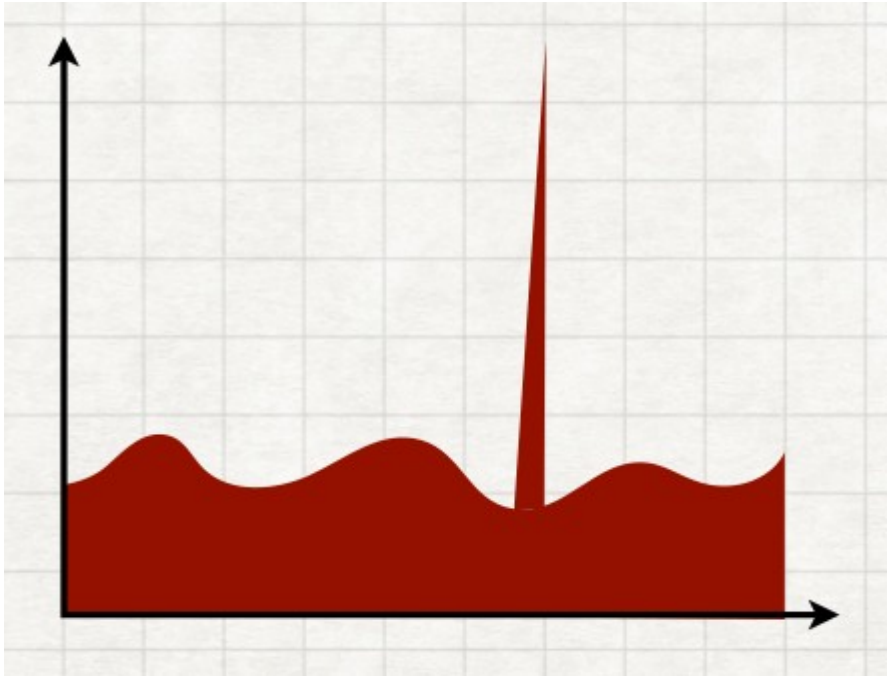
- Machine learning : data mining, predictive analytics, artificial intelligence (in practice : statistics and numerical methods for statistical analysis)

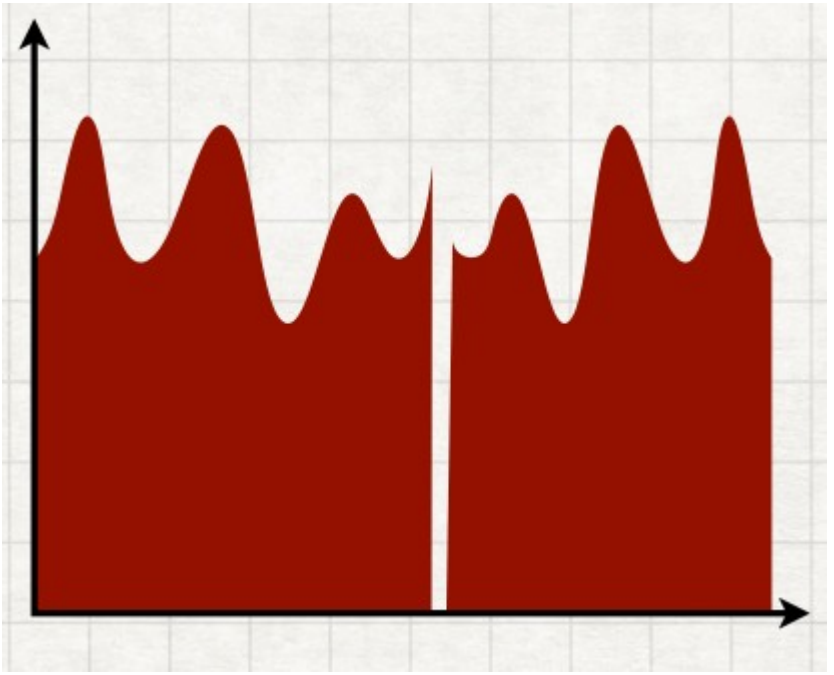
- Anomaly: deviation from “normal”/”expected”
  Anomaly=Outlier=Deviant or Unusual Data Point

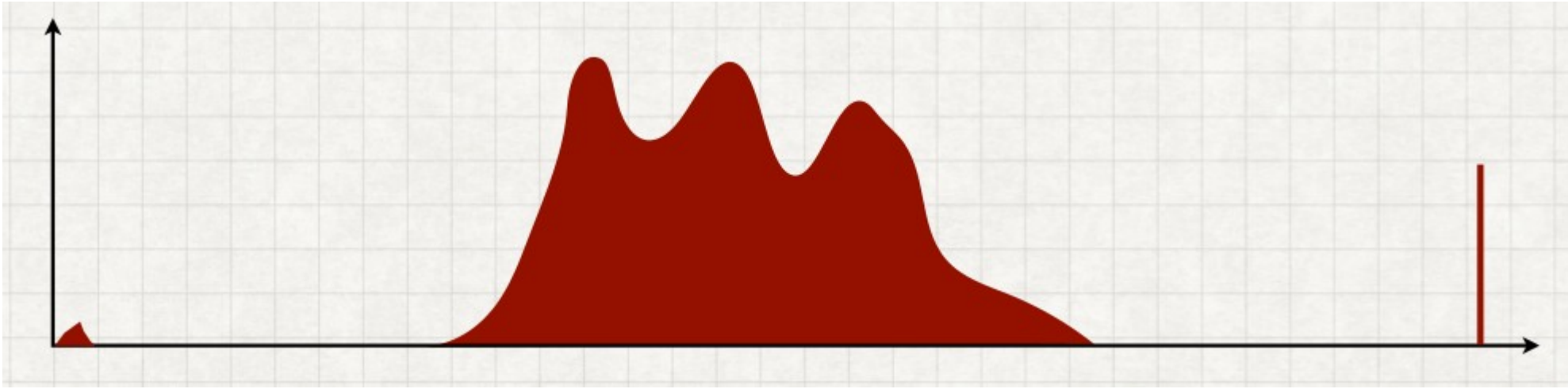
- Anomaly detection : detection of outlier events or observations: Detecting deviations from the expected pattern of a data set.

The real challenge in anomaly detection is to construct the right data model to separate outliers from noise and normal data.

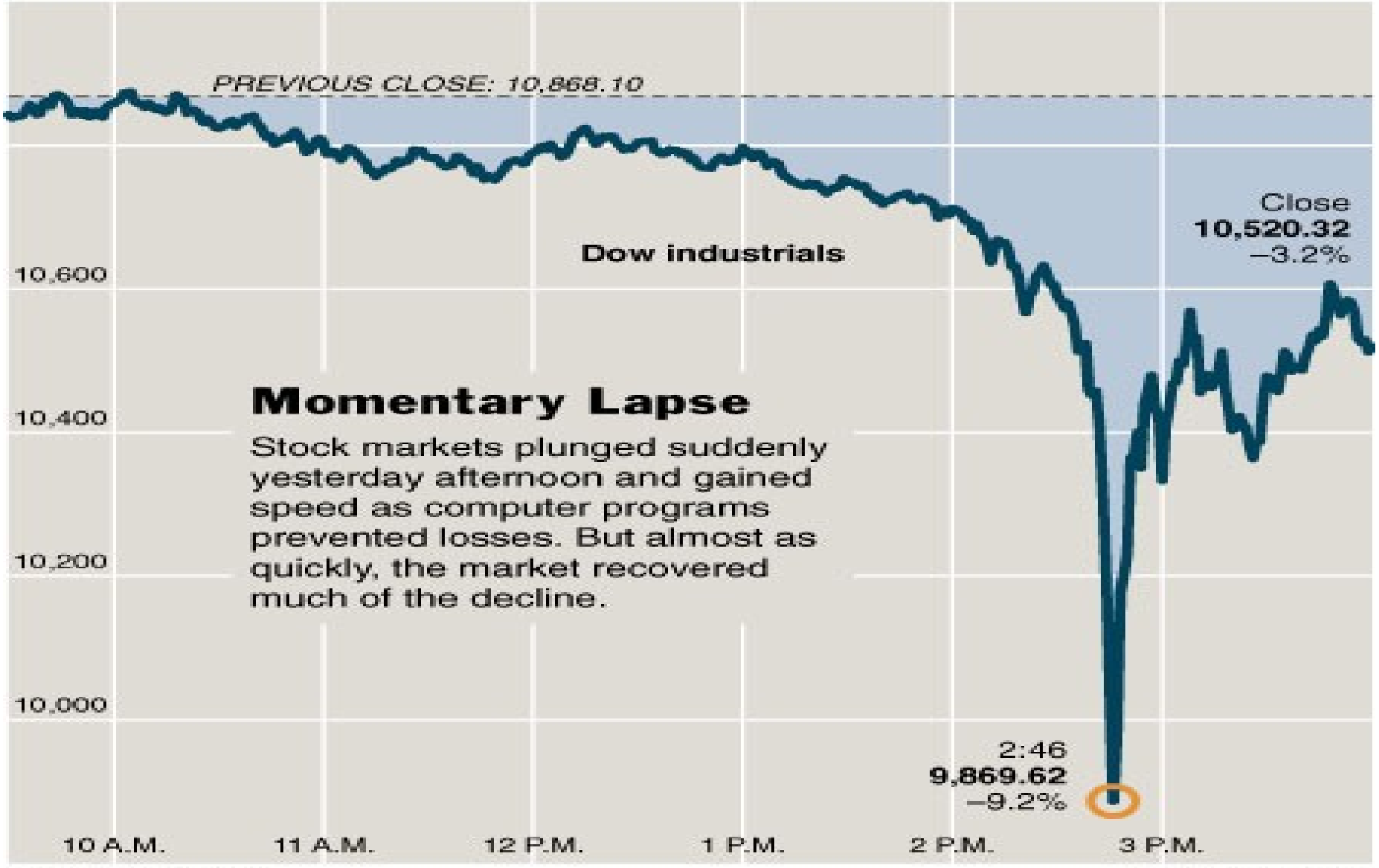
In one dimension: what anomalies look like?







Real Example: Stock market : The May 6, 2010, Flash Crash at 2:45 pm

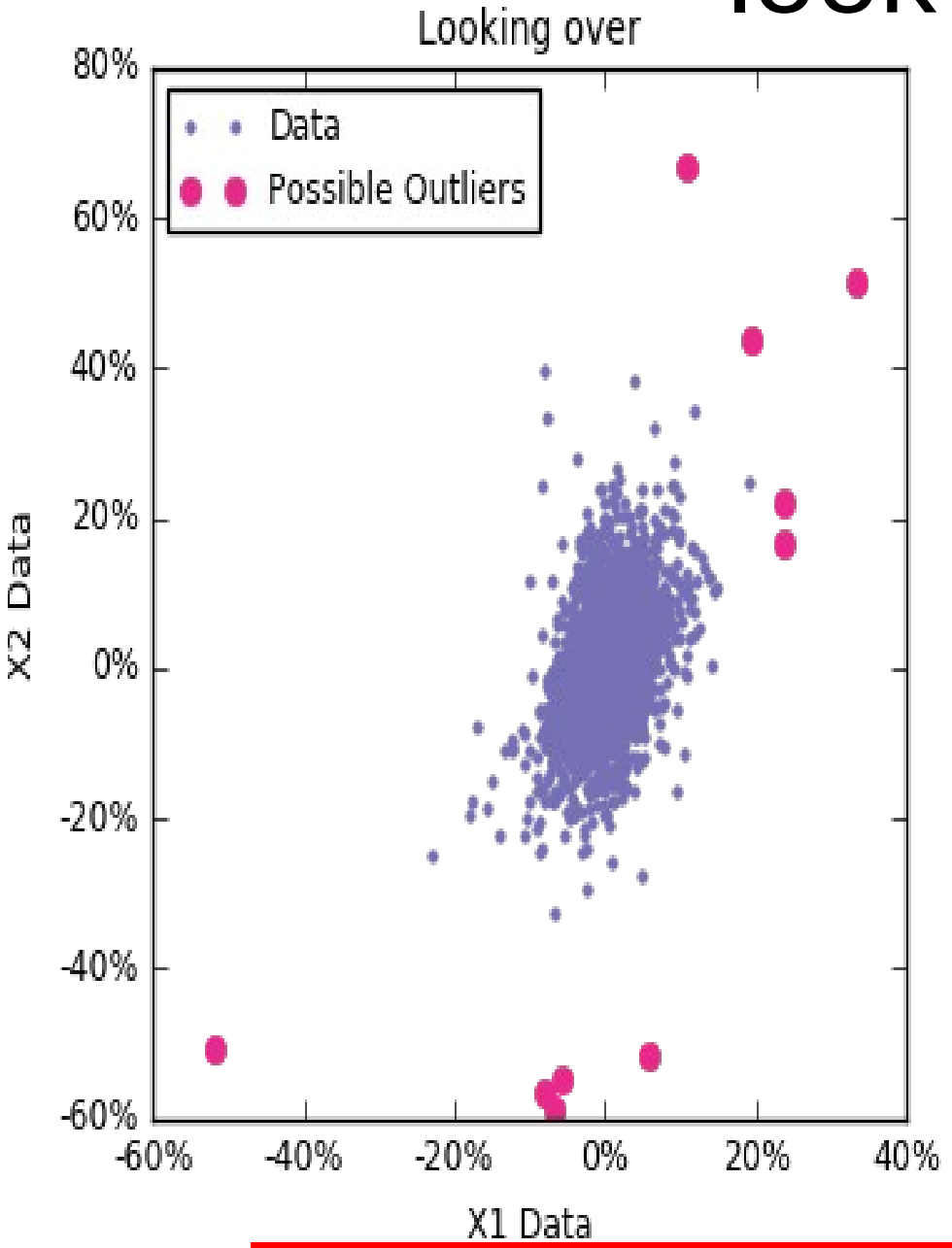


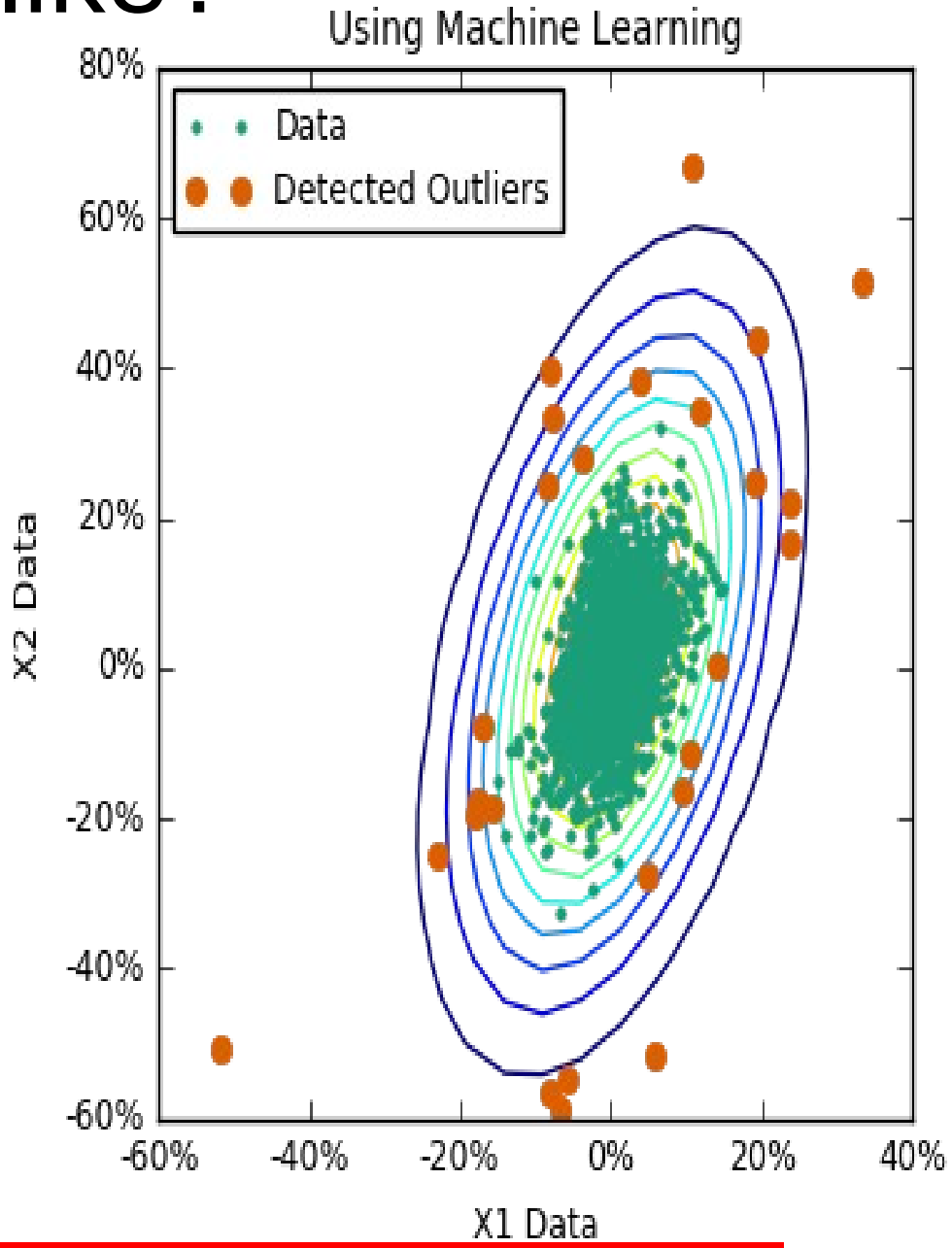
Real Example from the Stock market : A real financial fraud!

- On April 21, 2015, nearly five years after the incident, the U.S. Department of Justice laid "22 criminal counts, including fraud and market manipulation" against Navinder Singh Sarao, a trader. Among the charges included was the use of spoofing algorithms; just prior to the Flash Crash, he placed thousands of E-mini S&P 500 stock index futures contracts which he planned on canceling later.

Stock market : Flash Crash continues

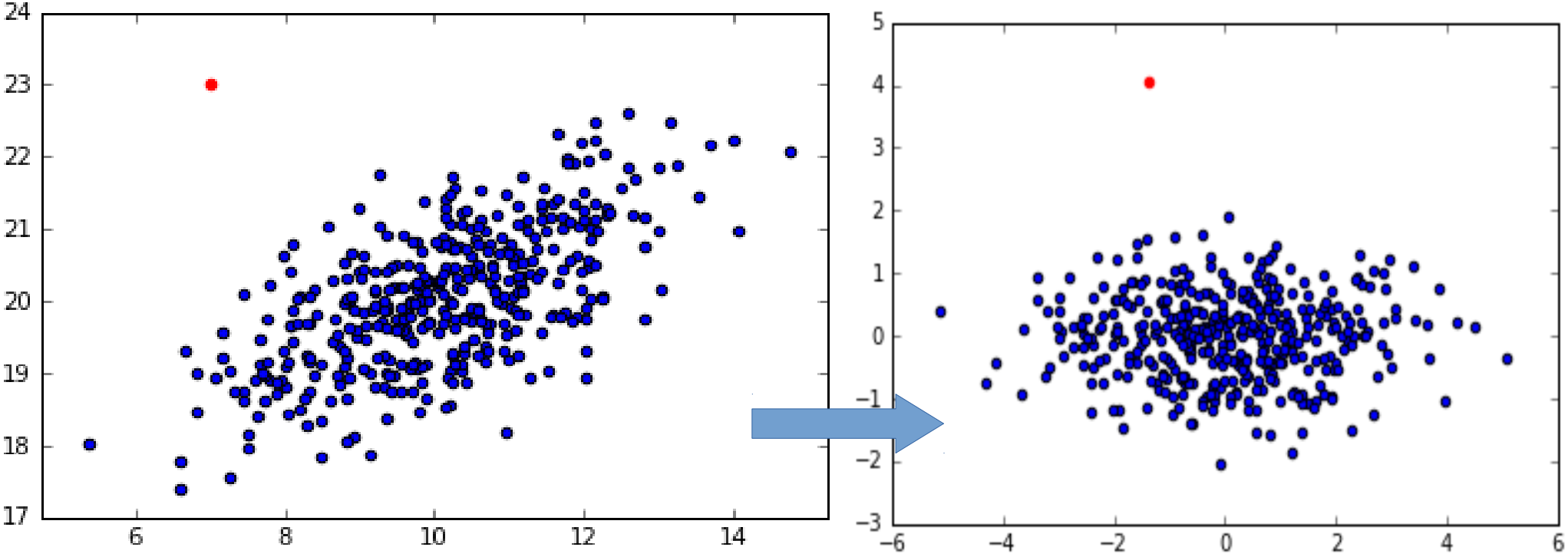
In two dimension: what anomalies look like?





Results with DBSCAN algorithm from sklearn.cluster

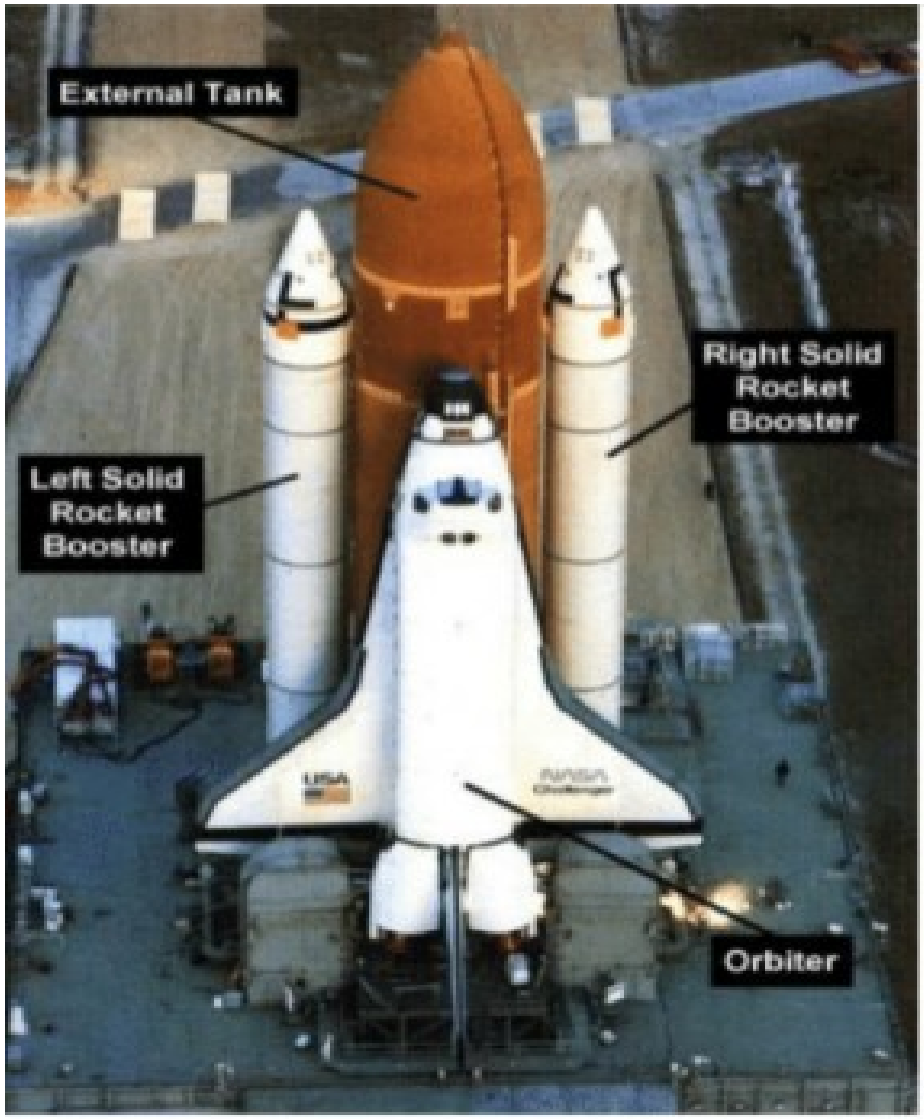
In two dimension: what anomalies look like?

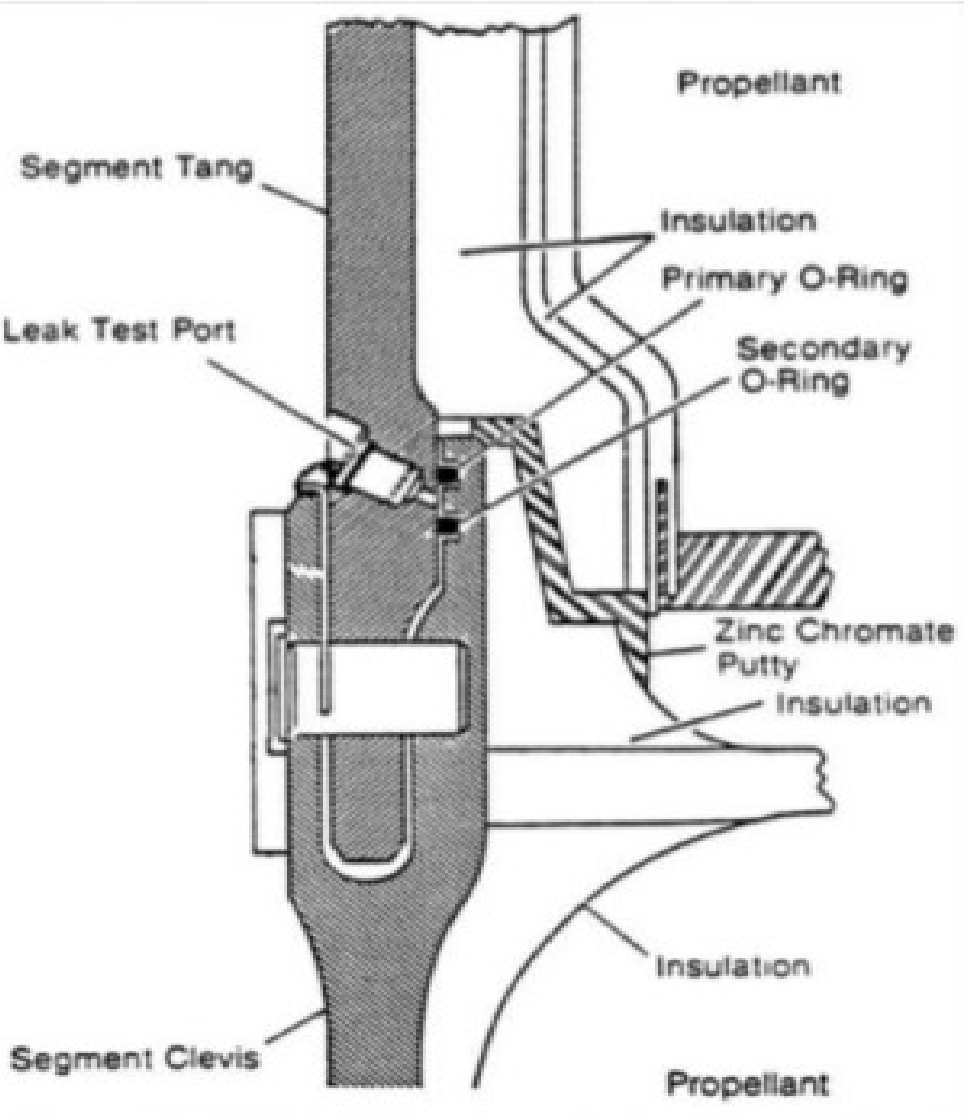


Results with 2D PCA method from sklear.decomposition
also you can do kernel PCA

Real Example: Rocket science

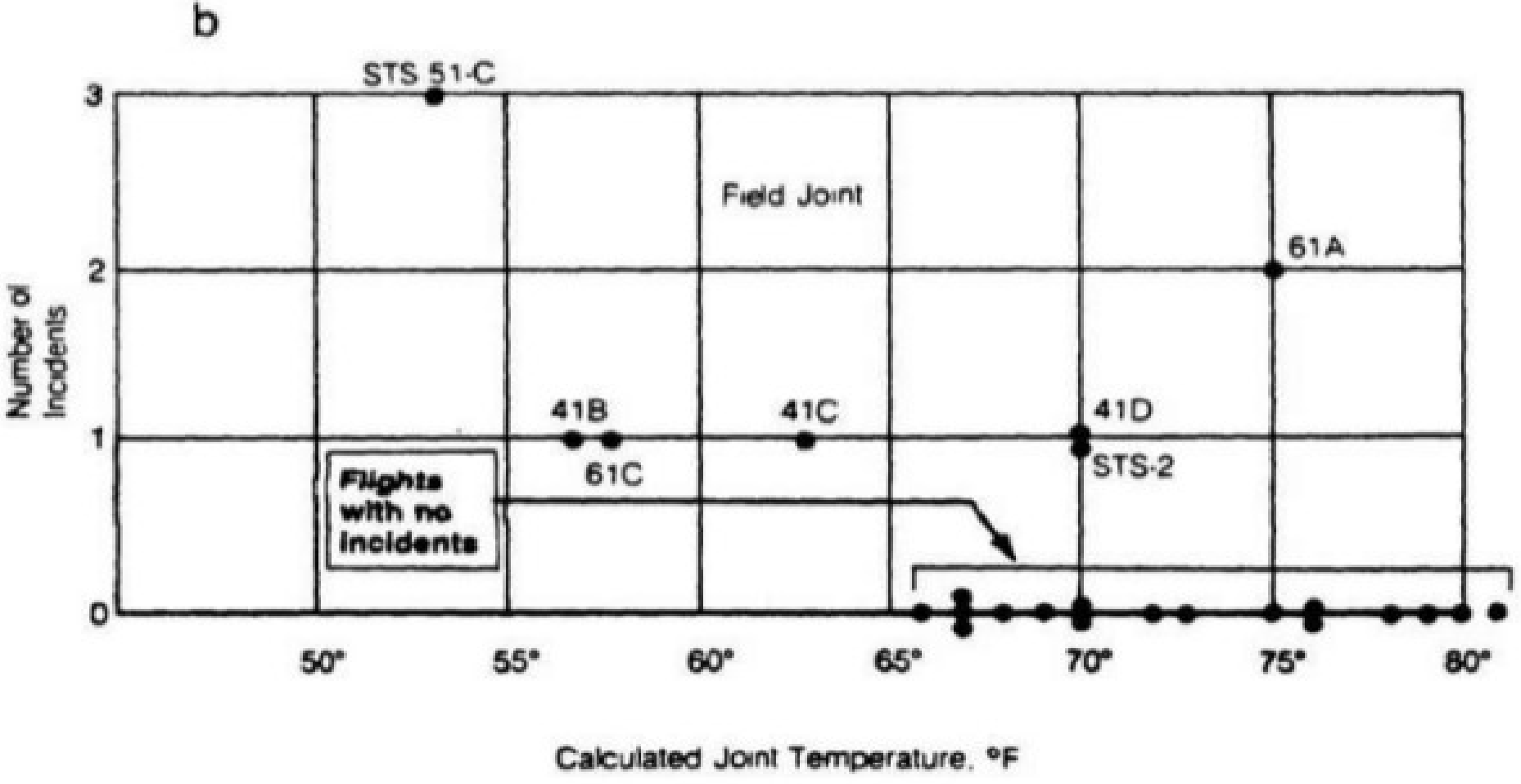
January 28 1986 Challenger spatial mission:
Dalal & al., 1989 Journal of the American Statistical Association



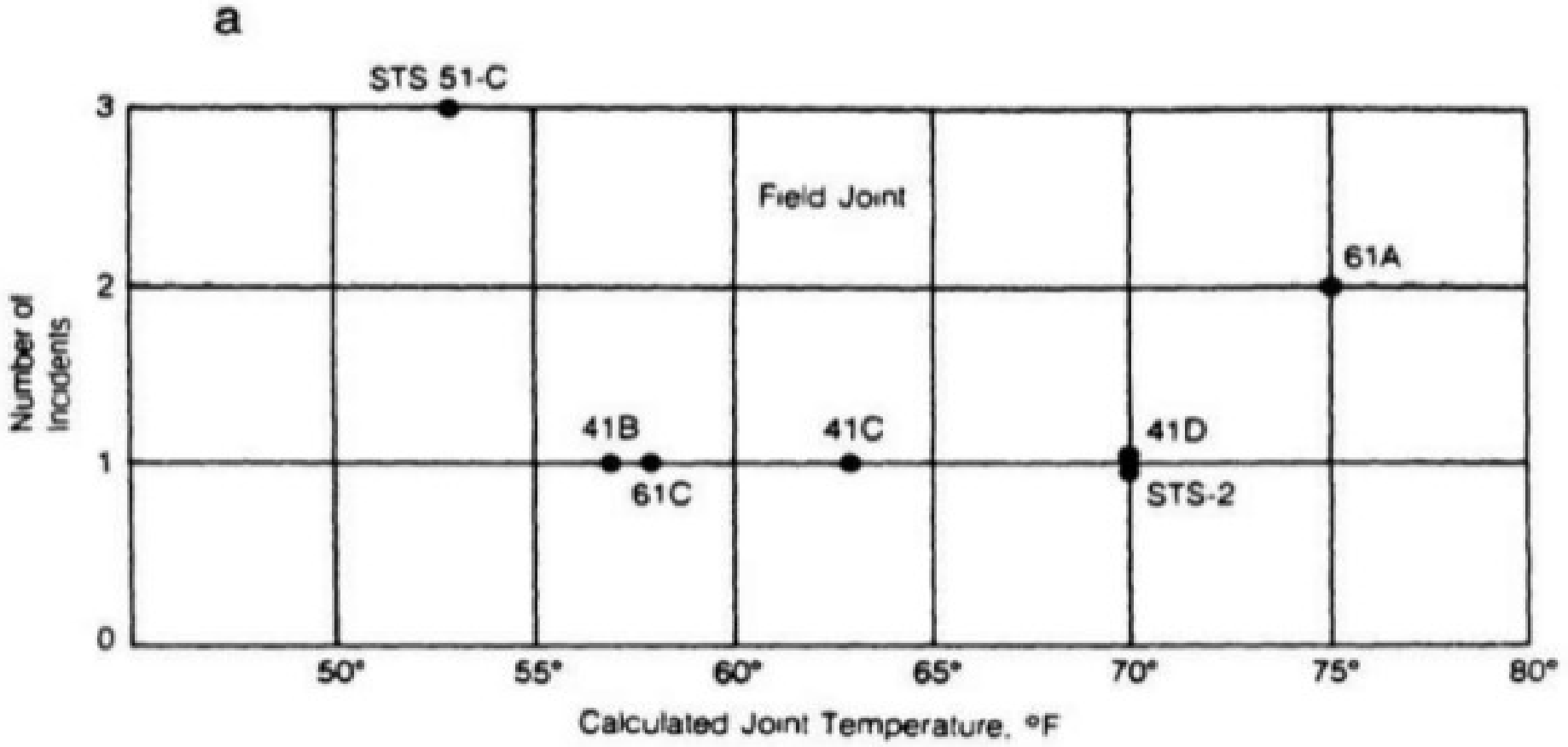


In two dimension: what anomalies look like?

Should have considered plot (b), which had data on 23 of the previous 24 flights.



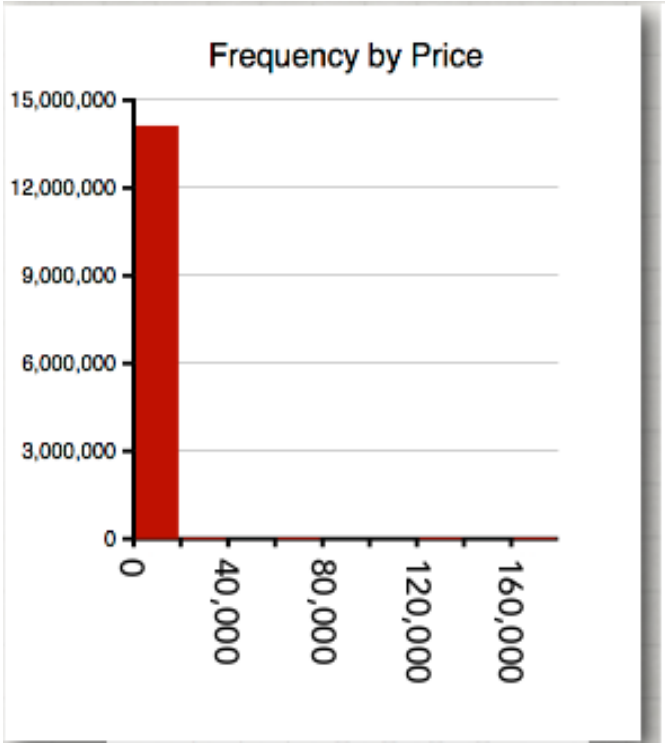
In two dimension: what anomalies look like?



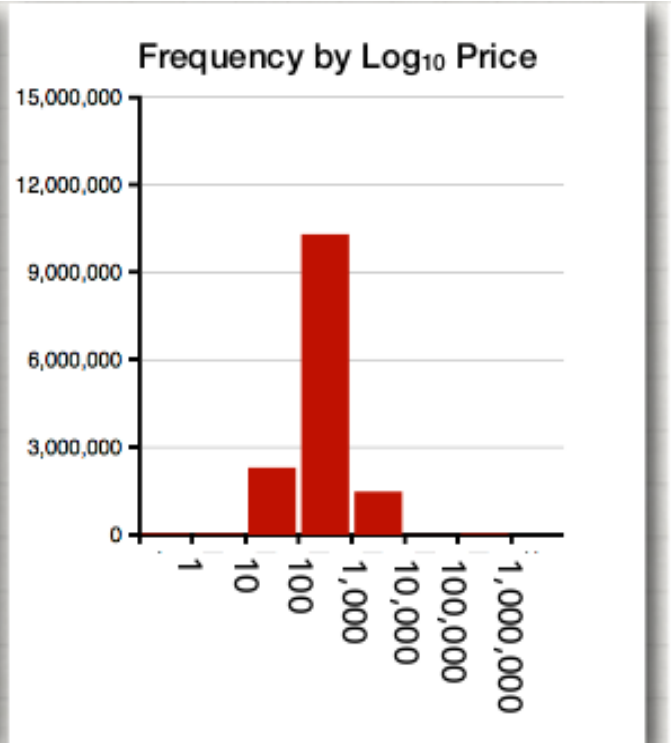
Based on plot (a), they concluded:

"Temperature data are not conclusive on predicting primary O-ring blowby."

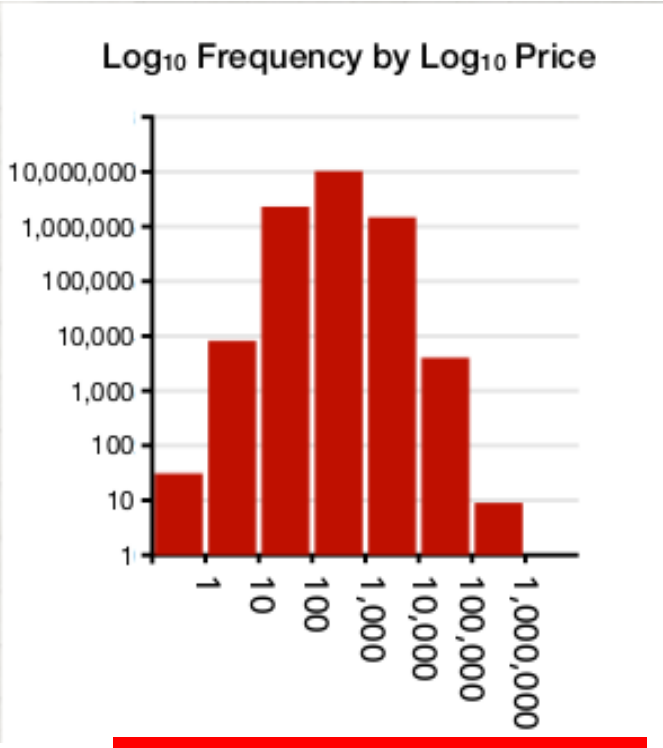
Using Logarithmic, log-log plots to display outliers can help



Linear histogram



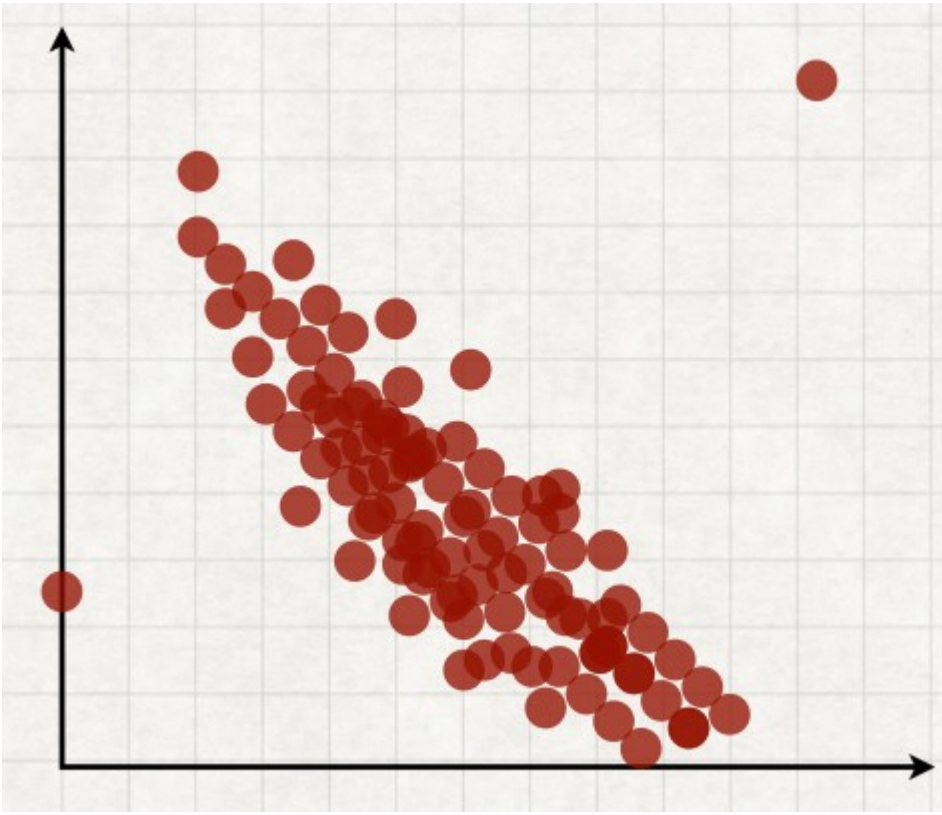
Frequency vs log10 Price



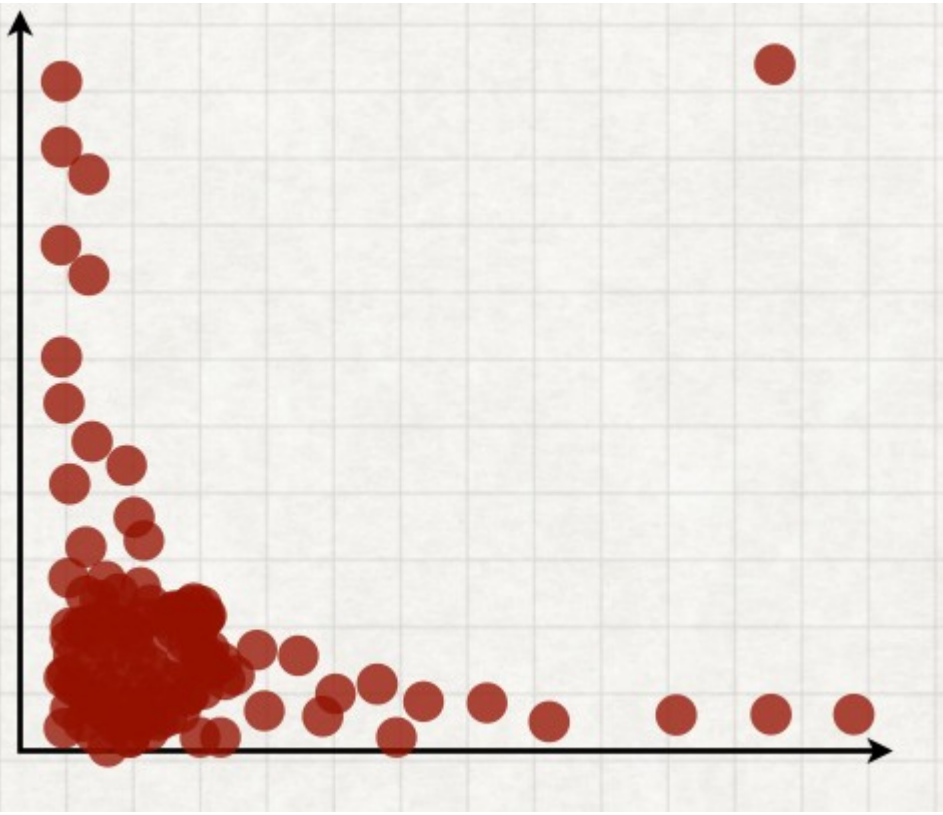
Log-log histogram log10 freq vs log10 price

pyplot.hist can "log" y axis for you with keyword argument log=True
Example : plt.hist(numpy.log10(data), log=True)

Using Logarithmic, log-log plots to display outliers can help



Linear plot



Log-log plot
matplotlib.pyplot.loglog

Outlier detection general applications

- Cyber security: Detect cyber-attacks on networks: more trusted connections
- Equipment failure (risk theory/théorie de la fiabilité) industrial sector
- Fraud detection
- Detecting cheaters in mobile gaming
- Preprocessing task for analysis or machine learning
- Reduce false declines then grow the revenue
- Detecting French regions where Le Pen’s scores at the 2017 presidential election deviate from predictions based on socio-economic variables (towardsdatascience)

Applications to financial sector (banking, insurance): Towards Fintech

- Retail bank: Credit card fraud
- Private bank: Market abuse, Anti-money laundering
- Investment bank: Market abuse (Flash Crash), Anti-money laundering
- Insurance companies: Fraudulent operations
- Central banks: detecting tax havens (panama papers)

Requires different approaches because Red flags are banking-type specific (specific business expertise)

Methodology?
Supervised learning vs. Unsupervised learning

Supervised vs. Unsupervised

- In credit card fraud detection one knows the target variable.

  How? Customers tell us. Can use supervised approach because the true class is self-revealing.

- In market abuse or money laundering detection we don’t really know classes (how money is laundered changes all the time and by the same criminal organisation)

Why supervised learning is difficult?

- Severe class imbalance : we estimate that 99.9% are trusted operations vs. 0.1% of fraudulent operations

- Problem during the train test split
- Solution you can use the stratification option in the train_test_split function of sklearn

And now why unsupervised is difficult?

- Sever class overlap : money laundering is mixed with legal financial activity, especially in Investment banks
- Uncertainty around the data model
- The complexity of data
- The huge volume of data (time complexity)

- Next we will discuss the data models
- To avoid time complexity: use dask, numba (used to speed numpy), ray and the newly module modin (used to speed pandas) + demonstration

Algorithms

- We can differentiate between three methods:

  - Distance based algorithms (similarity)

  K-NN for classification

  K-Means for clustering

  - Density-based (fitting a density)

  DBSCAN and HDBSCAN

  Local outlier factor (LOF)

  - Parametric

  Gaussian mixture models (GMM)

  Single class SVM

  Extreme value theory: Tukey outlier labeling

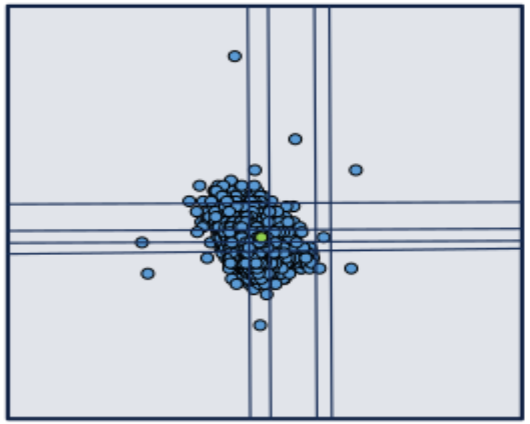
Tree ensemble algorithm : Isolation forest (used in Credit-swiss)

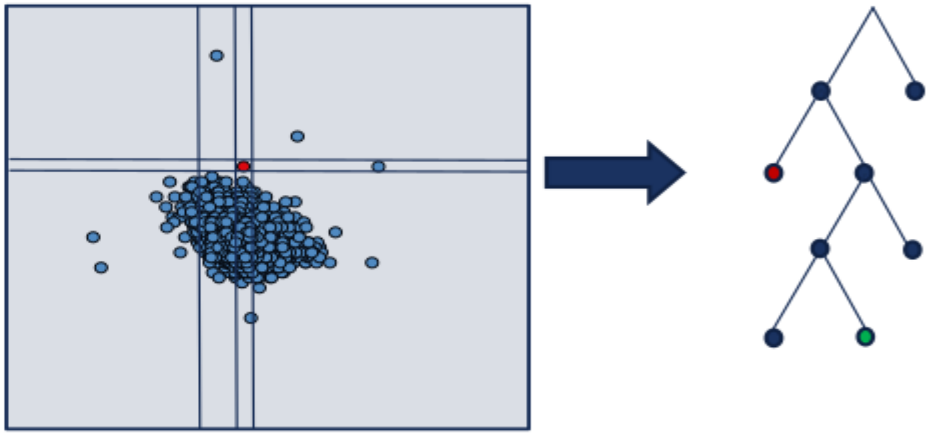
(F. T. Liu, et al., Isolation Forest, Data Mining, 2008. ICDM'08, Eighth IEEE International Conference)

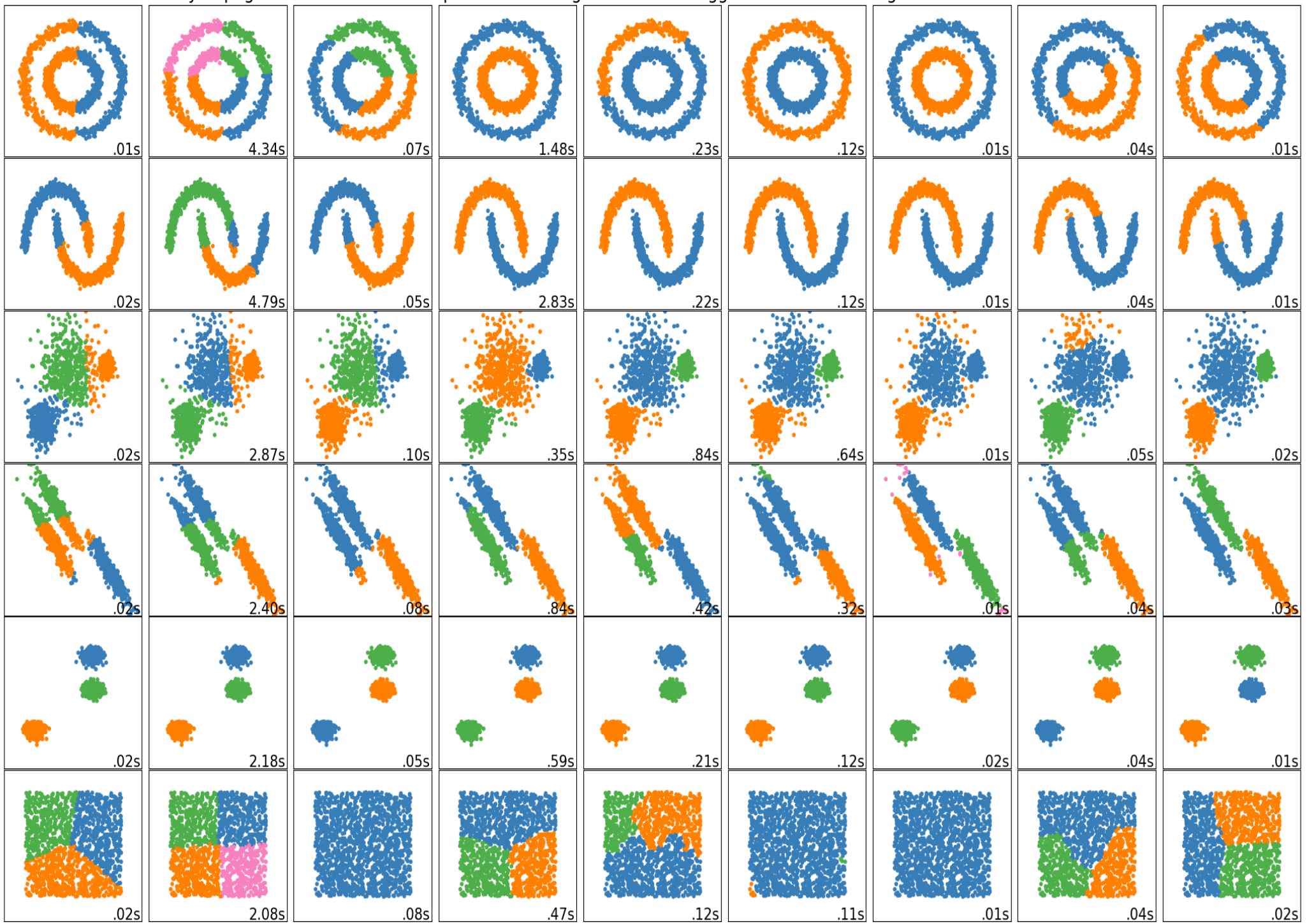
from sklearn.ensemble import IsolationForest

Ensemble regressor uses the concept of isolation to explain/separate-away anomalies

- No point based distance calculation
- Instead I.F. builds an ensemble of random trees for a given data set and anomalies are points with the shortest average path length






MiniBatchKMeans
AffinityPropagation
MeanShift
SpectralClustering
Ward
AgglomerativeClustering
DBSCAN
Birch
GaussianMixture
.01s
4.34s
.07s
1.48s
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Unsupervised learning for anomaly detection (conclusion)

- Unsupervised learning is all about finding structure in data
- Techniques: Clustering (K-means, spectral clustering)
- Principle Components Analysis
- Support Vector machine
- **Autoencoder Deep Neural Networks : DNN autoencoder anomaly detection (exotic)**
- Filtering, Sequential Bayesian Filtering
- Gaussian mixture Model clustering via EM
- **LightGBM (Exotic)**