Anomaly Detection

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Topics

1) Problems anomaly detection target
2) The curse of dimensionality
3) Global and Local Outlier Detection + Demos
4) High Dimensional Subspace methods + Demo
5) AutoEncoders
6) Actuarial Applications

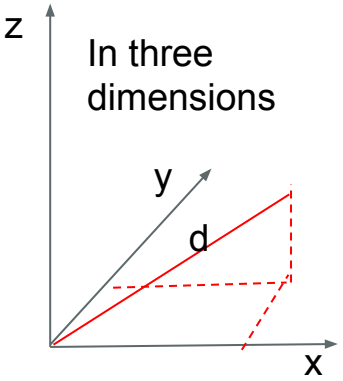
Problem statement for Actuaries

- A modern insurance company in 2017 has seen three great shifts over the last two decades
  - Waves of automation through the 90s and continuing through the 2010s in policy and claims systems leading to better data capture
  - Larger datasets and deeper information. Unstructured data making strides, first in text tagging and mining and now in image, natural language processing and audio processing
  - Supportive software (Apache) and hardware (GPUs) making the theoretical now practical
- Data generated from new systems now comes from several sources(read potentially different “mechanisms” or “data generating functions”).
- Actuaries need to make decisions on these sources for pricing, claims and fraud detection (http://www.casact.org/community/affiliates/camar/1016/De_Jones.pdf)

➢ How do we know that the **a) rules and models we use, works for most of the data** and b) **are there other effects in the data that we are missing and c) what doesn’t fit to the general data distribution; potentially from another process?**

Curse of dimensionality part 1/2

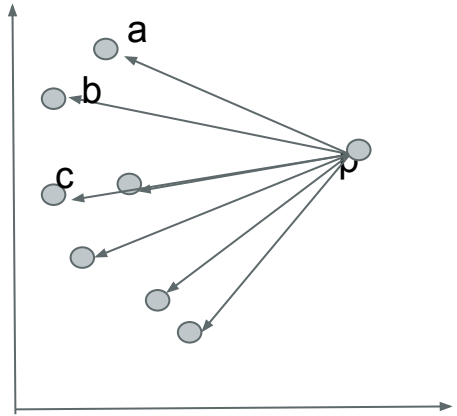
- **Before we get to answer these questions, we have a problem.**
  - Outlier detection depends on distances and relationships between datapoints
  - Distances are easy to calculate in a few dimensions, but increasingly difficult in multiple dimensions



Euclidean distance
d^3 = x^3 + y^3 + z^3

Distance measures are a research topic themselves. Here are two of the most popular

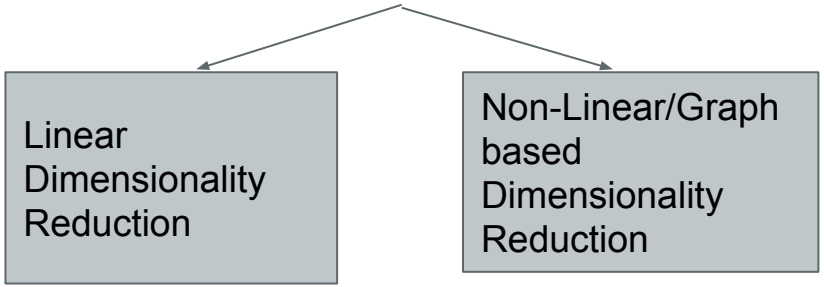
- Euclidean Distance (left): measures the linear distance between the point and in this case the origin. We measure if a point is far away
- Angular distance(right): measures the angle from one point to the remaining and claims outliers present if the angles are similar



Angle based outlier =
Var(ap,cp)/(ap^2 * cp^2)

Curse of dimensionality part 2/2

- **Before we get to answer these question, we have another problem.**
  - Distance and Angle approaches work well in low dimensions and one can compare points well enough
  - In high dimensions the distance from one point to another reaches equity. Therefore as dimensions increase, data needs to be added: This is the curse of dimensionality. Since we may not have more data, we observe sparsity.
- You guessed it: we have dimensionality reduction techniques at hand to help



Dimensionality Reduction

Dimensionality Reduction is a large research topic but the goal is to reduce a set of points in high dimension to a lower dimension for and before analysis

Common linear approaches include: PCA/rPCA, Linear Discriminant Analysis,

Non-linear approaches include: ISOMAP, t-SNE, Diffusion Maps, Neural Nets: Autoencoders

In business context: simplifying the number of drivers one explores for an outcome (risk, severity, suspicion of fraud) can save time and money

➢ **Let's look at code and demos for each in R**

Global and Local Outlier Detection 1/2

Definition 1 :"An outlier is an observation that deviates so much from other observations as to arouse suspicion is was generated by a different mechanism" ~ Hawkins. **Definition 2:** An object p in a dataset D is a DB(pct, dmin)-outlier if at least percentage pct of the objects in D lies greater than distance dmin from p, i.e., the cardinality of the set {q Î D | d(p, q) dmin} is less than or equal to (100 - pct)% of the size of D.~Brenuig

Colloquial use cases:

Outlier detection: *"We want to smooth the data for analysis " (an older perspective)*

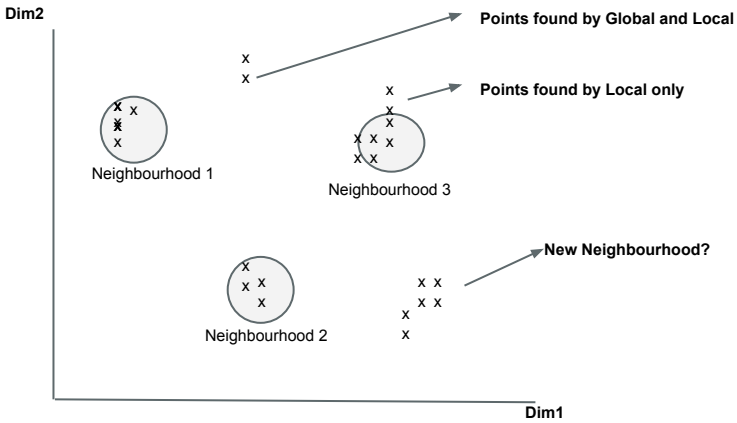
Anomaly detection : *"We want to classify data that is rare and different from the expected data generating process or identify issues with the process"*

Applied Fraud/Intrusion Detection: *"We want to identify individuals or groups that are behaving suspiciously"*

K-NN Anomaly Detection R Demo : Distance Based Outliers

Global and Local Outlier Detection 2/2

Goals of Local Outlier Factor detection: "Use the k neighbours from initial analysis and find distance measures from neighbourhood to local outlier; finding points that differ to neighbourhood"



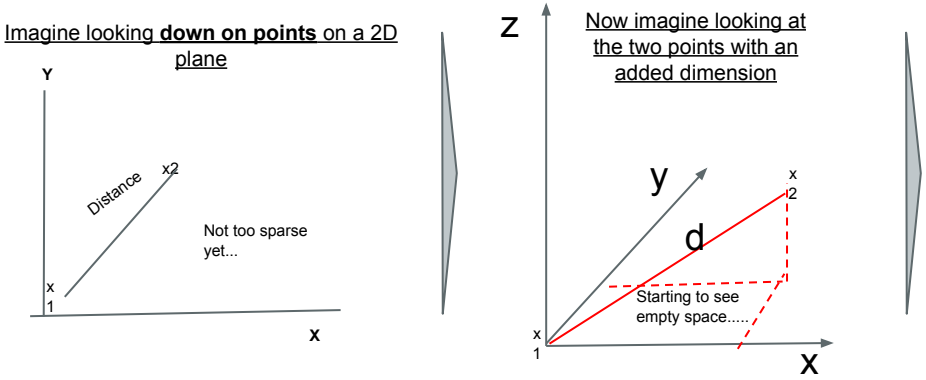
1) Each point is compared to their neighbourhood
2) A local Distance is calculated with respect to the neighbourhood

LOF Detection R Demo: Density Based Outliers

Detection in High Dimensional Space

“Sparse dataset”: A dataset where the distances between points are roughly equal, data is not clustered in high dimensions, instead usually in isolation with *space* in between.

Goal: Sparsity in insurance data increases as we add dimensions and importantly, unstructured data: especially text. *How can an insurance application such as Claims or UW leakage adjust to this growing trend?*



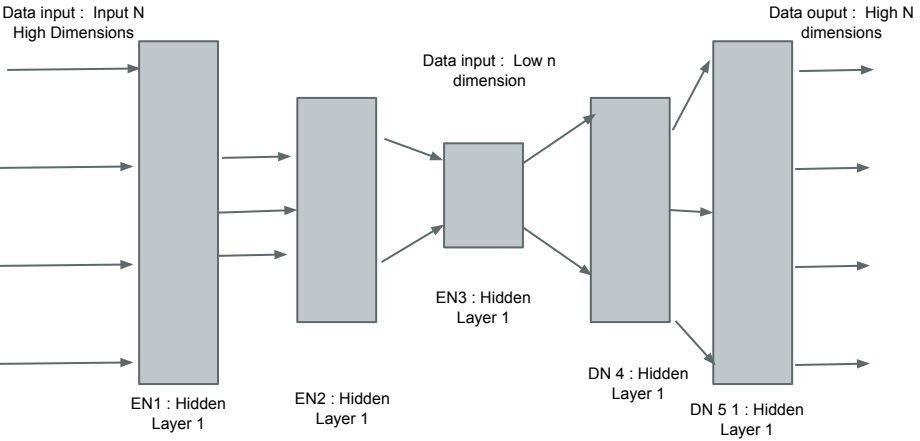
Euclidean distance
d^2 = (x2-x1)^2 + (y2-y1)^2

Euclidean distance
d^3 = x^3 + y^3 + z^3

R Demo - Subspace Outlier techniques

Demo using Apache Spark and H2O

Data Flow through a 5 layer AutoEncoder



- An autoencoder is a neural net that reduces the dimensions by sucessively fewer functions in hidden layer
  - Encoding the high Dimensional input Data N into small n dimensions in hidden layers
  - Decoding the low dimensional representation back to high dimensions
- Standard testing of the reconstruction: Compare predicted output to input
- An example of non linear, high dimensionality reduction
- Works for unstructured data : encodes images, text, audio

R Demo - Autoencoder

References

Papers

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