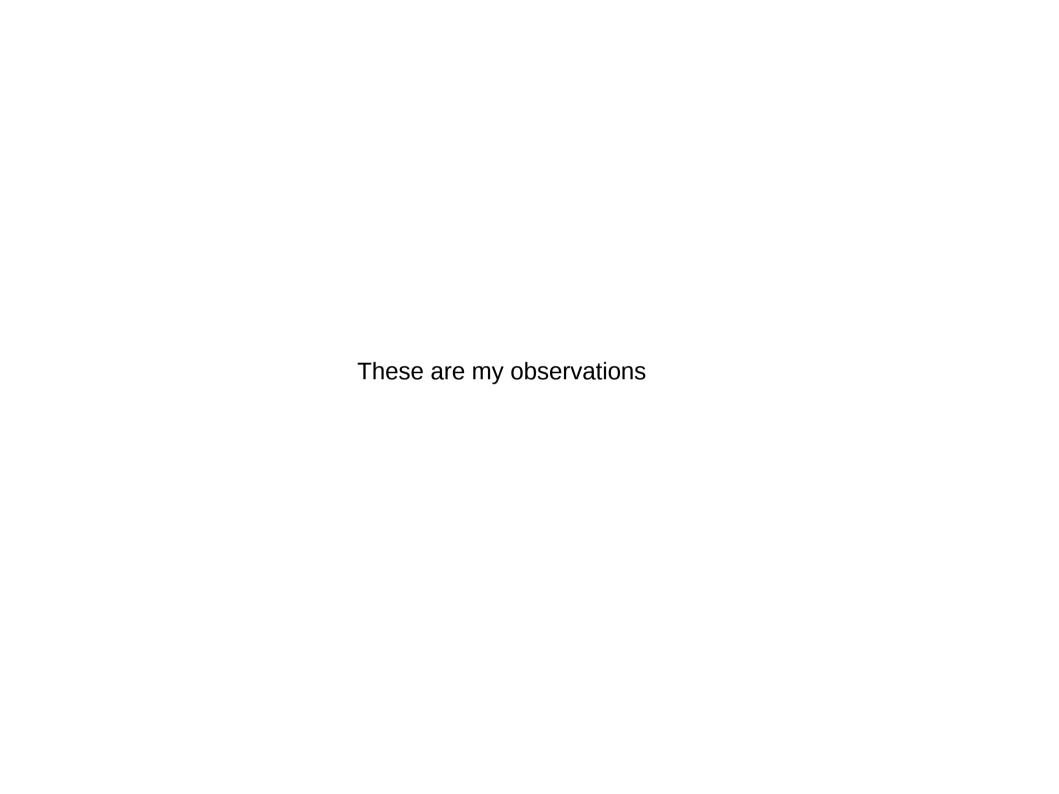
Before and After Deeplearning

Shaukat Abidi



Classification (Discrete classes)

- Naive Bayes
- Logistic Regression
- Support Vector Machines
 - Binary SVM
 - Multiclass SVM
- Applications: text classification, image classification, etc

Classification (structured classes)

- Support Vector Machines
 - Structured SVM (like SVM-HMM)
- Conditional Random Fields
- Applications: NER and POS (NLP), Video frames tagging

Regression

- Linear Regression
- Support Vector Regression
- Applications: stock-price prediction etc

Clustering

- K-means
- Gaussian Mixture Models
- Applications: Topic modeling, Image segmentation, bag-of-words in computer vision



Car(1) or no car(0)?



Feature Engineering

- SIFT
- DSIFT
- HOG
- Filters
- etc



Feature Engineering

- SIFT
- DSIFT
- HOG
- Filters
- etc

Classifier

- SVM
- NB



Feature Engineering

- SIFT
- DSIFT
- HOG
- Filters
- etc

Classifier

• SVM — Final Classifier

NB



Spam email(1) or Normal email(0)?



Feature Engineering

- N-Grams
- Bag-ofwords
- Linguistic knowledge



Feature Engineering

Engineering

- N-Grams
- Bag-ofwords
- Linguistic knowledge

Classifier

- SVM
- NB



Feature Engineering

- N-Grams
- Bag-ofwords
- Linguistic knowledge

Classifier

- SVM Final Classifier
- NB

- Classification (Discrete classes)
 - Multilayer Perceptron or Simple Feed-Forward Network
 - Convolution Neural Net
 - Example: Text classification, Image Classification

- Classification (Structured classes)
 - Recurrent Neural Nets
 - LSTM cells
 - GRU cells
 - Example: NER, POS and technically video sequence classification

Regression

- Multilayer perceptron (remove sigmoid and change loss function to regression loss)
- Applications: stock-price prediction etc

Clustering

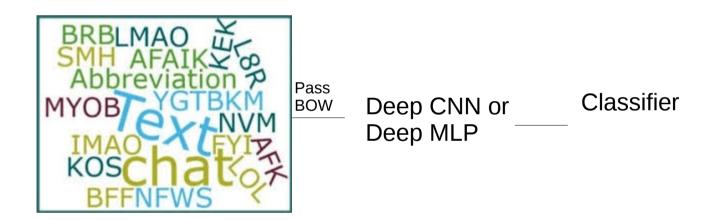
- Autoencoders
- Applications: dimensionality reduction or latent representation



Pass raw pixels

DEEP CNN — Final Classifier

The model will learn rich representation in deeper layers (guided by loss function)



The model will learn rich representation in deeper layers (guided by loss function)

Multimodality

– Possible with Traditional Methods?

Multimodality

- Possible with Traditional Methods?
- Multimodal Example: Caption generation





Encoder (Deep architecture of your choice)

Decoder ——

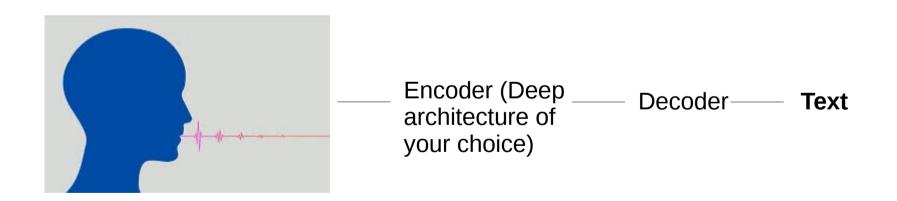
Your caption

Generation using Seq-to-Seq models

 Example: Translation, NER, and I hope segmentation while converting speech to text

Generation using Seq-to-Seq models

 Example: Translation, NER, and I hope segmentation while converting speech to text



Getting rid of feature engineering

 Example: Pass the raw input (Image pixels) and beef-up the network

Getting rid of feature engineering

 Example: Pass the raw input (Image pixels) and beef-up the network



Pass raw
pixels
DEEP CNN —— Final Classifier

The model will learn rich representation in deeper layers (guided by loss function)

Merger with different fields

 Example: Bayesian methods in Deep learning (Variational Autoencoders)

Merger with different fields

 Example: Bayesian methods in Deep learning (Variational Autoencoders), Deep Reinforcement Learning

Summary

- DL methods dominate the application areas where big amount of data is easily available (for instance NLP and CV)
- Problem formulation is simple for majority of applications
- Challenge lies in the training of such deeper and deeper models