# Module 1 – Part I

# Welcome to the Deep forecasting course!

## What is Time Series Forecasting?


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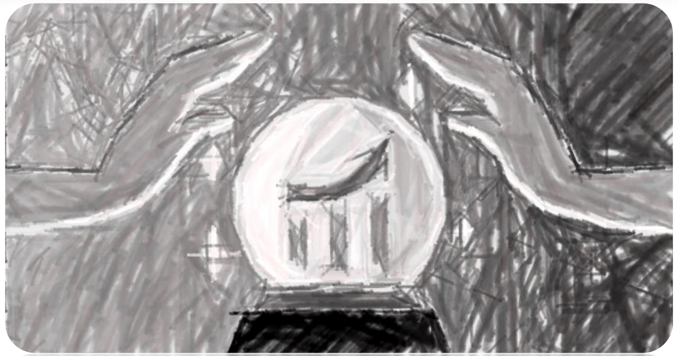
# What is Forecasting?

- Forecasting has fascinated people for thousands of years!

> *Tell us what the future holds, so we may know that you are gods.*
> *Isaiah 41:23 700 BC*



- Forecasting is about predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact the forecasts.

- Forecasts could be **short-term**, **medium-term** or **long-term.**

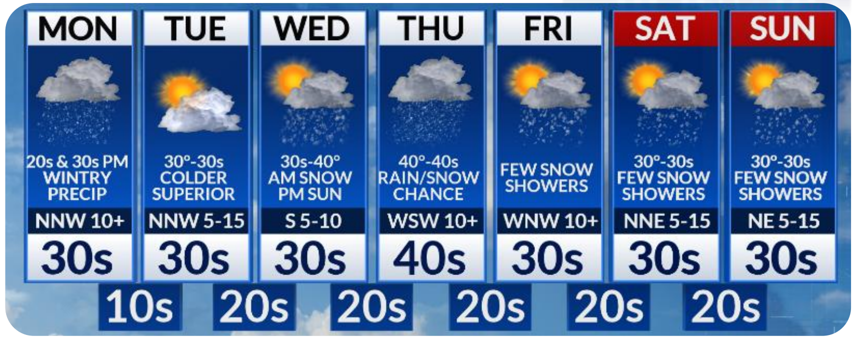
# Quantitative vs Qualitative Forecasting

| | Quantitative Forecasting | Qualitative Forecasting |
|---|---|---|
| Data sources | Numeric data and statistical analysis | Expert opinions, subjective judgment, or other non-numeric data |
| Accuracy | Can be more accurate when large amounts of reliable data are available | May be less accurate than quantitative methods, but can still be useful when data is difficult to measure numerically |
| Suitability | Suitable for forecasting phenomena that can be easily measured and tracked | Suitable for forecasting subjective or hard-to-measure phenomena |
| Flexibility | Rigid and less flexible; relies on specific data and statistical techniques | More flexible and allows for the incorporation of expert judgment and other subjective factors |
| Examples | Stock prices, sales revenue, market demand for a stablished product, weather forecast, population growth | Fashion trends, market demand for a new product, employee performance |

# More Forecasting examples

- Which of the following examples are easier to forecast?

1. Time of sunset this day next month
2. Apple stock price in 6 months
3. Apple stock price tomorrow
4. EURUSD exchange rate next week
5. Airline ticket demand next year
6. Airline ticket prices next year
7. US presidential election 2024
8. Monthly rainfall in Utah next winter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# What Impacts Forecastability?

- How do we say something is easier to forecast?
- Forecastability factors are:
  - Data Availability
  - How similar the future is to the past!
  - Good understanding of the underlying factors

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# Explanatory vs Timeseries vs Mixed models

| Model | Example |
|---|---|
| Explanatory (Cross sectional) | $\mathrm{P} = f(\frac{P}{E}, \frac{P}{S}, size, \frac{B}{M}, GDP, CPI, \ldots, u)$ |
| Timeseries | $P_{t+1} = \mathrm{f}\,(\mathrm{P_t}, \mathrm{P_{t-1}}, \mathrm{P_{t-2}}, \ldots, \mathrm{u})$ |
| Mixed (dynamic regression, panel) | $\mathrm{P_{t+1}} = f(\frac{P_t}{E_t}, \frac{P_t}{S_t}, size_t, \frac{B_t}{M_t}, GDP_t, CPI_t, \ldots, u_t)$ |

- In this course we focus on Timeseries models because:

1. We may not know all the underlying factors!
2. Extremely difficult to know or forecast the future value of many factors when forecasting the variable of interest
3. We are more interested in predictability rather than explanatory power

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# Basic steps in a forecasting task

**Step1**: Problem definition

- Forecasting type and horizon (one-step, multi-step, multi-output forecasts), …

**Step 2**: Data Collection

- Time horizon, structural changes, data type, …

**Step 3**: Exploratory Analysis

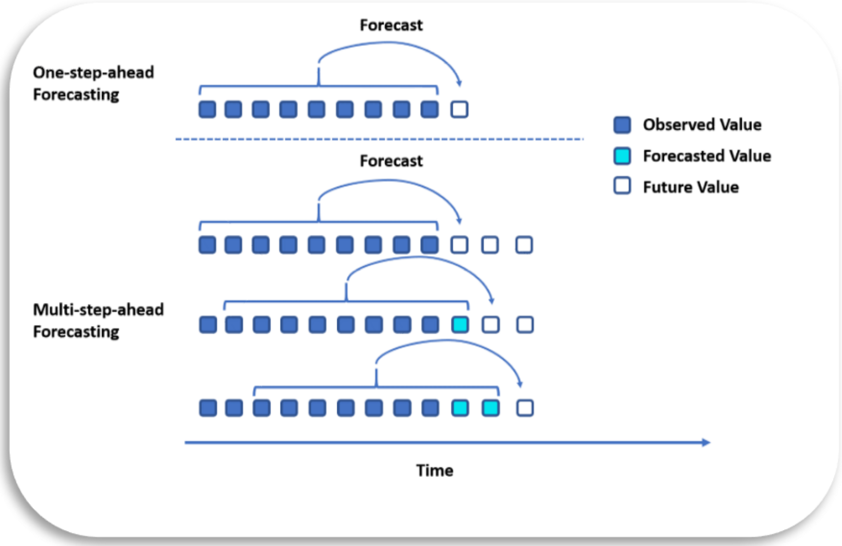
- Trend, seasonality, outliers, …

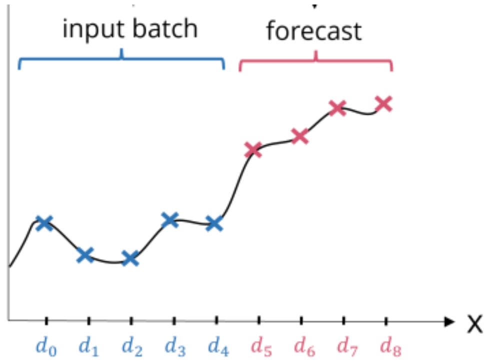
**Step 4**: Model Selection and Training

- Traditional **vs** machine learning **vs** deep learning

**Step 5**: Model Evaluation and Comparison

- MSE, RMSE, MAE, $R^2$, MAPE, sMAPE, …

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# Forecasting notation

$$\hat{y}_{t+h|t} = f(y_t)$$

- $y_t$ itself can be decomposed into different components (level, trend, seasonality)
- Fitted values at time $t = 1 \ldots T$, are $\hat{y}_{t|t-1}$ ($h = 0$)
- One-step ahead forecast at time $T + 1$ ($T$ last observation in train data) and $h = 1$.
- Multi-step ahead forecast: $h = 2, 3, 4, \ldots$
  - One-output at a time
  - Multi-output at once

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | T=10 | 11 | 12 | 13 | 14 | 15 |

Train

Forecast

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# What is Time Series analysis and why it matters?

- Time series analysis is a powerful tool for understanding and predicting trends and patterns in data that are collected over time.
- Time series analysis is also useful for business decision makers, as it can help them to forecast future trends and make informed decisions based on data trends and patterns.
- **Why?**
  - Time series data is everywhere!
  - Better career opportunities,
    - Up to 90% of companies need better forecasting and
    - Less than 5% of data scientists are competent in time series analysis.
  - Hedge against next recession!


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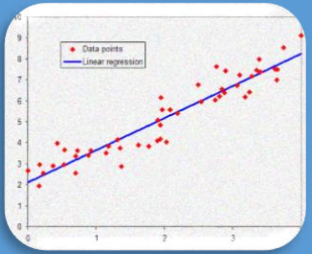
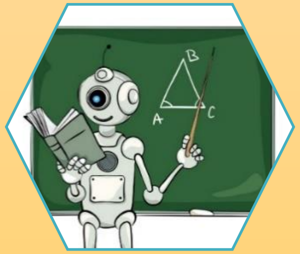
# What is our approach to time series analysis?

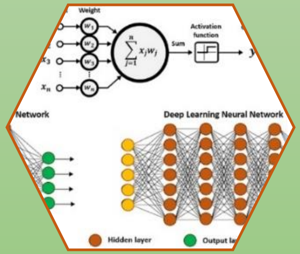
Econometrics




Machine Learning

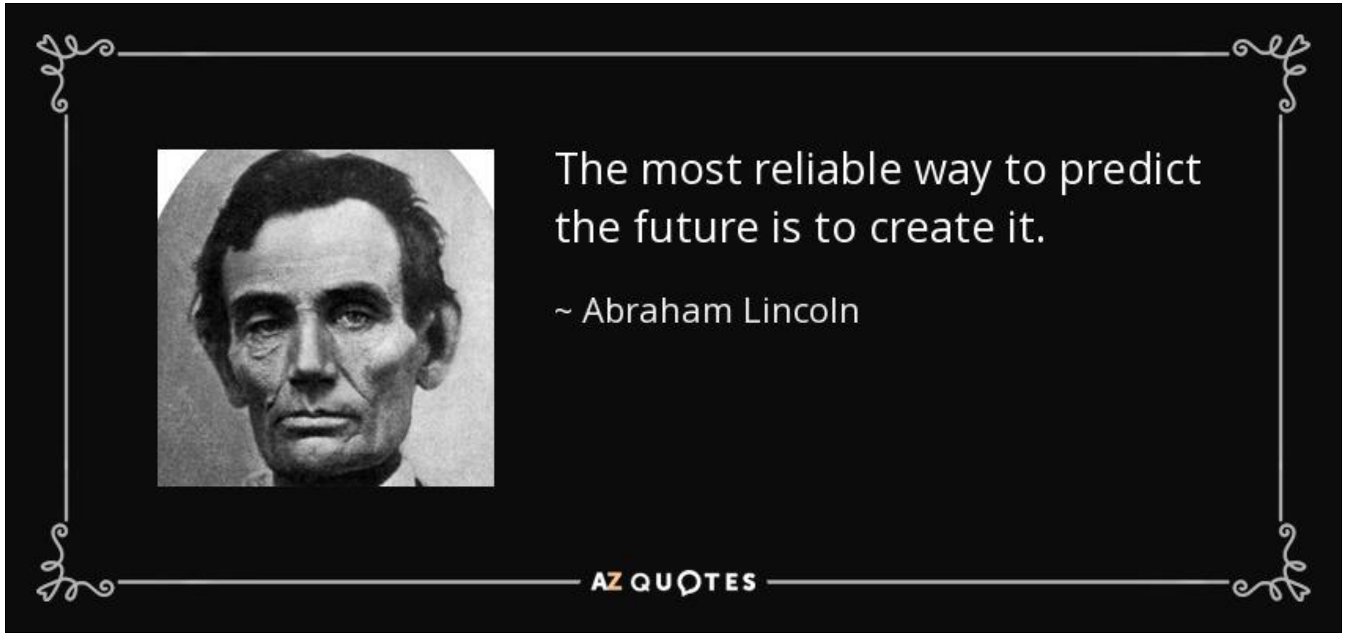



Deep Learning




Deep Forecasting

# Forecasting is not always easy!



# Road map!

- Module 1- Introduction to Deep Forecasting
- Module 2- Setting up Deep Forecasting Environment
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- Module 4- ARIMA models
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- Module 7- Deep Sequence Modeling (RNN, LSTM)
- Module 8- Transformers (Attention is all you need!)
- Module 9- Prophet and Neural Prophet

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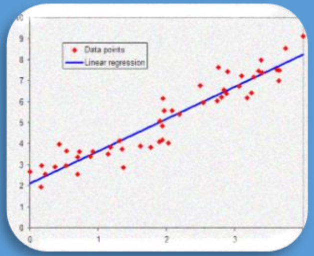
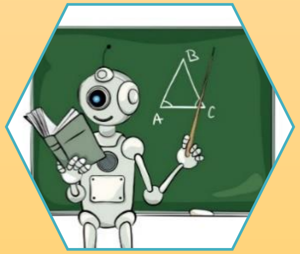
# Module 1 – Part II
# What is Deep Forecasting?

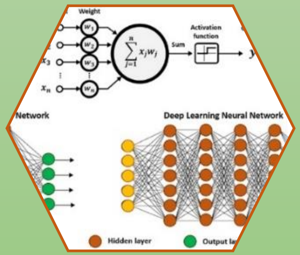
Econometrics




Machine Learning



Deep Learning




Deep Forecasting

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# Big picture: Econometrics vs Machine Learning and Deep Learning

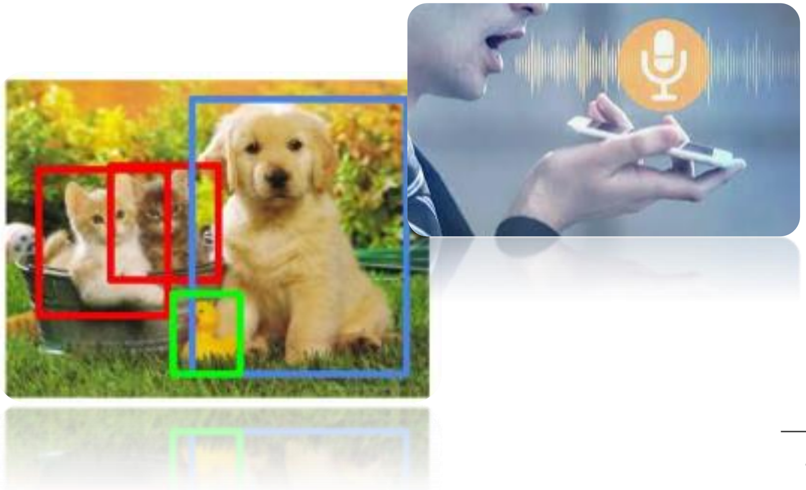
What are we trying to do as researchers?  Solve real world problems, right?

Is there a theory?

1- What is the relationship between

- Quantity demanded and price / income / technology / price of competitors / … ?
- Wage and education/ age/ gender/ experience/ …?

2- How about these problems? Object detection, Image Captioning, voice recognition, machine translation, and …



# A simple example


- Quantifying wage components! (is there a theory?)
- What are the drivers:
  - Demographic variables: Education, age, experience, IQ, …
  - Social and cultural variables: Ethnicity, race, gender, …
  - Job characteristic variables: Industry, location, working hours, …
- Let's build a model (assuming a linear functional form!)

$$wage = \beta_0 + \beta_1 educ + \beta_2 age + \beta_3 exper + \beta_4 IQ + \cdots + \beta_k hours + u$$

- ➢ Can you **interpret** this model? Do you care about the interpretability?
- ➢ Can you make **predictions** using your model?
- ➢ Can you make this functional form more flexible? What are the caveats?

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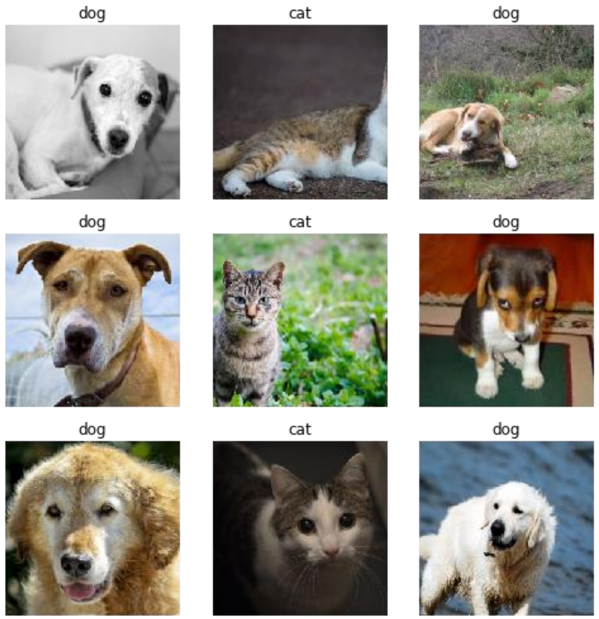
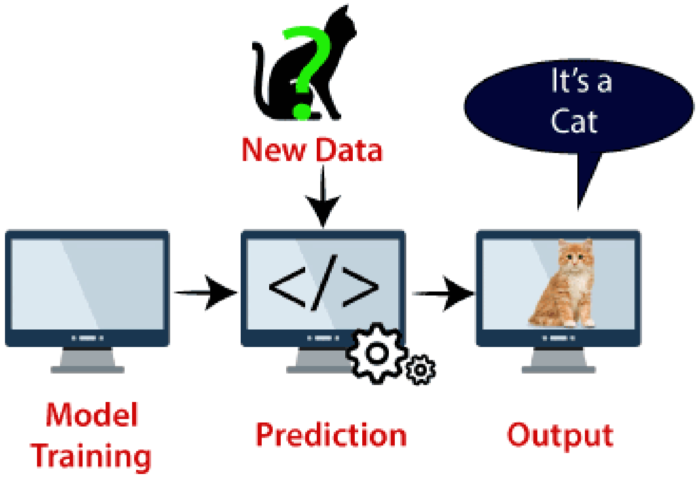
# A different example

- Cat vs dog classification problem (image recognition)




➢ Do you really care about interpretability of the model here?

➢ What about accuracy of your predictions?

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# Statistical learning vs machine learning

| | Statistical Learning | Machine Learning / Deep Learning |
|---|---|---|
| Focus | Hypothesis testing & interpretability | Predictive accuracy and extracting complex patterns |
| Driver | Math, theory, hypothesis | Fitting data |
| **Data size** | Any reasonable set | Big data |
| **Data type** | Structured | Structured, unstructured, semi-structured |
| Dimensions / scalability | Mostly low dimensional data | High dimensional data |
| Strength | Understand **causal** relationship & behavior | Prediction (forecasting and nowcasting) |
| **Interpretability** | High | Medium to Low |

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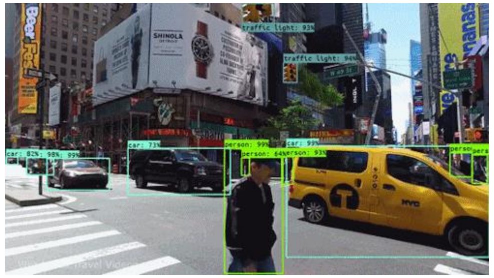
# Limitations of Econometrics/Structured ML

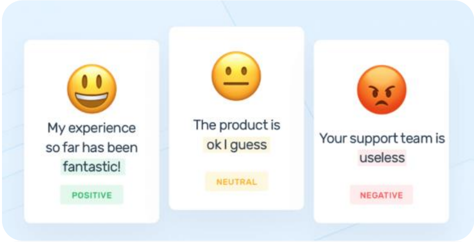
**Econometrics/structured ML can only handle structured data (tabular data)!**

## Structured Data

| | A | B | C | D |
|---|---|---|---|---|
| 1 | Date | Account | Transaction Type | Amount |
| 2 | 2017-01-12 | 123 | Credit | 6089.78 |
| 3 | 2017-01-12 | 123 | Fee | 9.99 |
| 4 | 2017-01-12 | 456 | Debit | 1997 |
| 5 | 2017-01-12 | 123 | Debit | 20996.12 |
| 6 | 2017-01-13 | 123 | Debit | 17 |
| 7 | 2017-01-13 | 123 | Debit | 914.36 |
| 8 | 2017-01-14 | 789 | Credit | 11314 |
| 9 | 2017-01-14 | 789 | Fee | 9.99 |
| 10 | 2017-01-14 | 456 | Debit | 15247.89 |
| 11 | 2017-01-14 | 123 | Debit | 671.28 |
| 12 | 2017-01-15 | 456 | Credit | 5072.1 |
| 13 | 2017-01-15 | 456 | Fee | 9.99 |
| 14 | 2017-01-16 | 456 | Debit | 5109.07 |
| 15 | 2017-01-19 | 123 | Credit | 482.01 |

## Unstructured Data
(everything else!!)

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# A more complex example

## Stock price prediction $$$

- What are the classical drivers:
  - Company’s fundamentals (balance sheet, income statement, cash flow statement)
  - Competitors (comparing multiples)
  - Technical analysis!
  - Seasonality (holidays, months, days, …)

What else?

- Market sentiment (news, tweets, blogger opinions, conference calls, …)
- Satellite images from parking lots!

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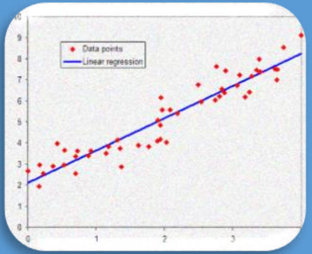
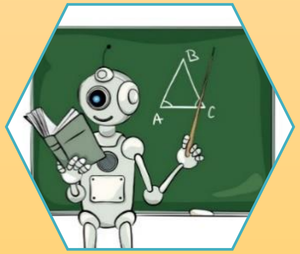
# What is our approach to time series analysis?

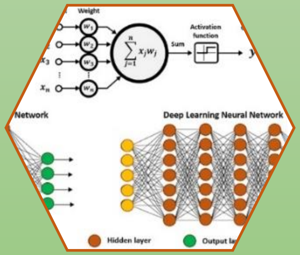
Econometrics




Machine Learning



Deep Learning

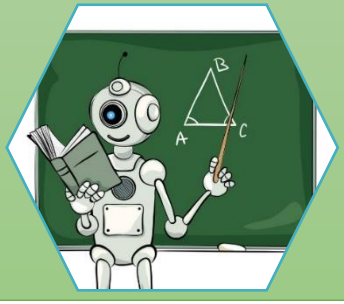



Deep Forecasting

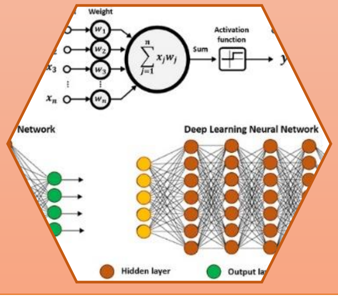
# Artificial intelligence vs Machine learning vs Deep learning

**Artificial intelligence:** Any technique which enables machines to mimic human behavior

**Machine Learning:** Subset of AI that enables computers to learn from data. the model is trained with a set of algorithms




**Deep Learning:** Subset of ML that extract patterns from data using neural networks.




1950's 1980's 2010's

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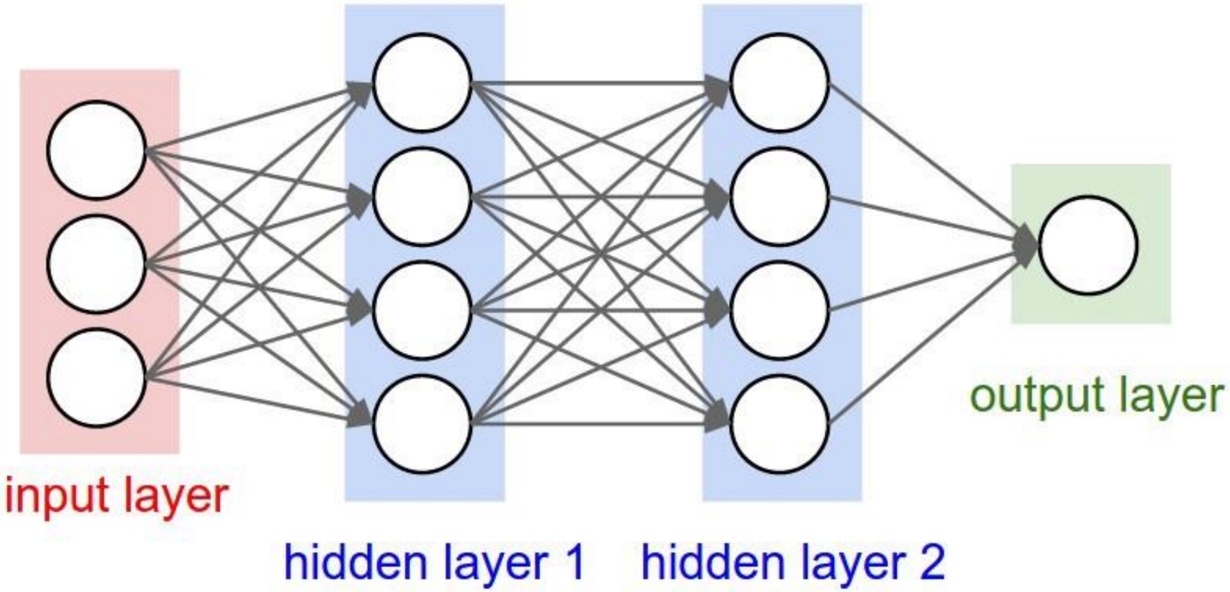
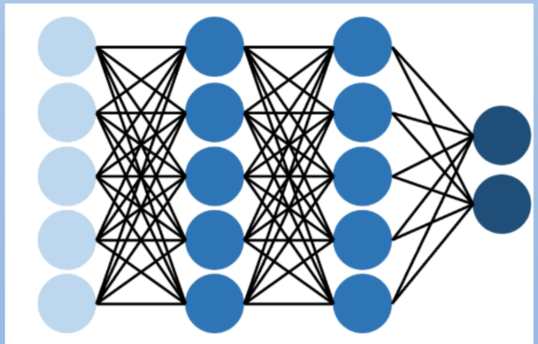
# What is Deep Learning?

- Deep learning is a type of machine learning that uses multiple layers of neurons to process data
- The goal of deep learning is to build a model that can automatically learn complex patterns from the data and make accurate predictions or decisions

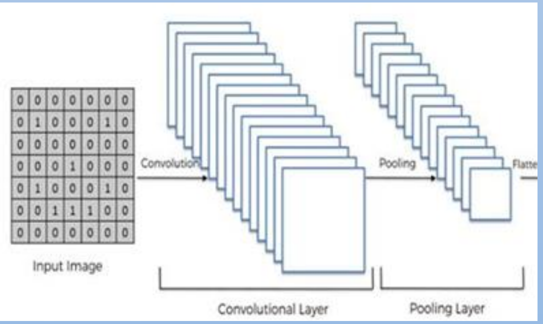


# Network examples

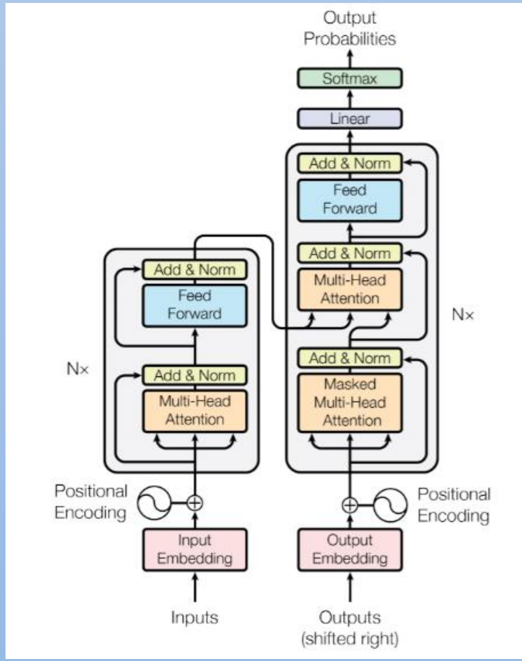
## Standard NN



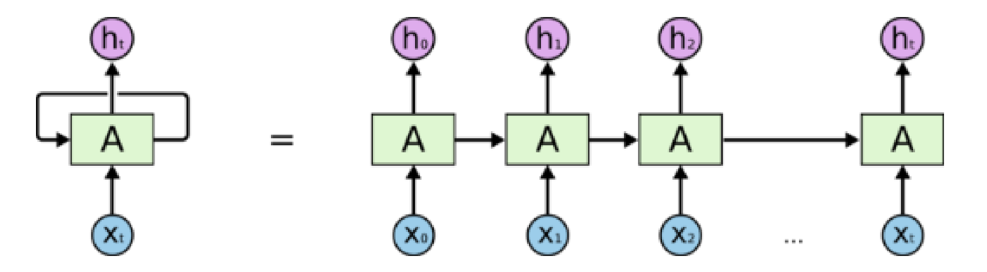
## Convolutional NN




## Transformers

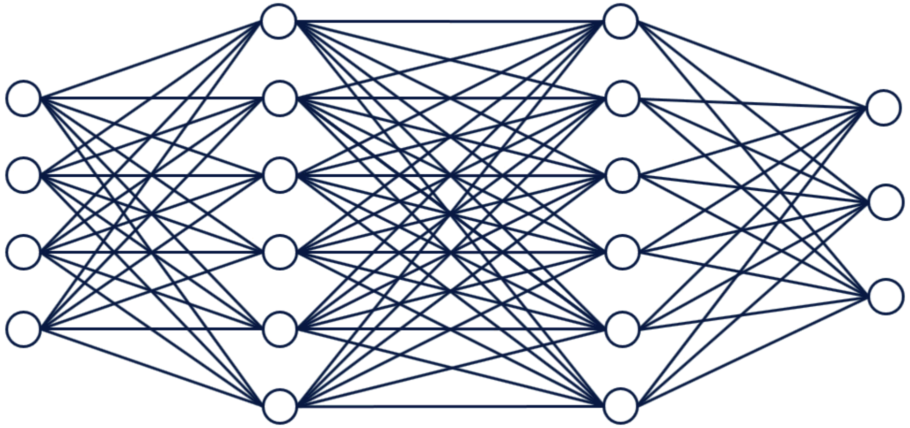



## Recurrent NN



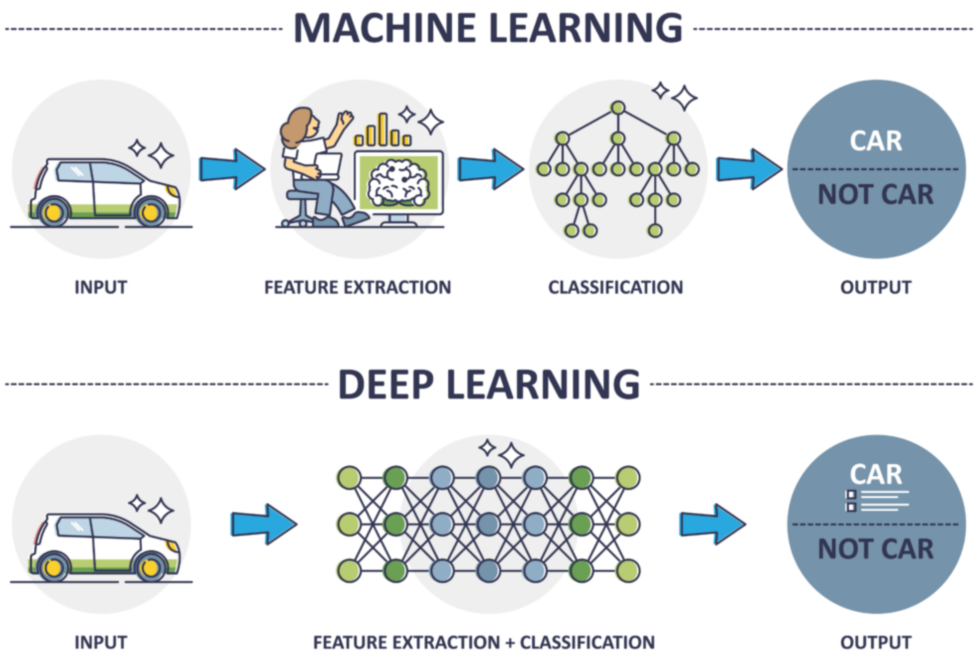
# How Deep Learning Works?

- The network uses a series of interconnected layers, with each layer transforming the input and passing it on to the next layer
- The final layer of the network produces the output, which is compared to the true output label to evaluate the performance of the network
- The network is then adjusted to minimize the difference between the predicted and true output labels, and the process is repeated until the network has learned to make accurate predictions on new, unseen data



# Why Deep Learning?

- In deep learning, the model is not explicitly programmed with a set of rules or algorithms, but instead learns to recognize patterns and make predictions by adjusting the connections between the neurons in the network!
- Can learn the underlying features directly from data and in a hierarchical manner. No feature extraction/engineering required!

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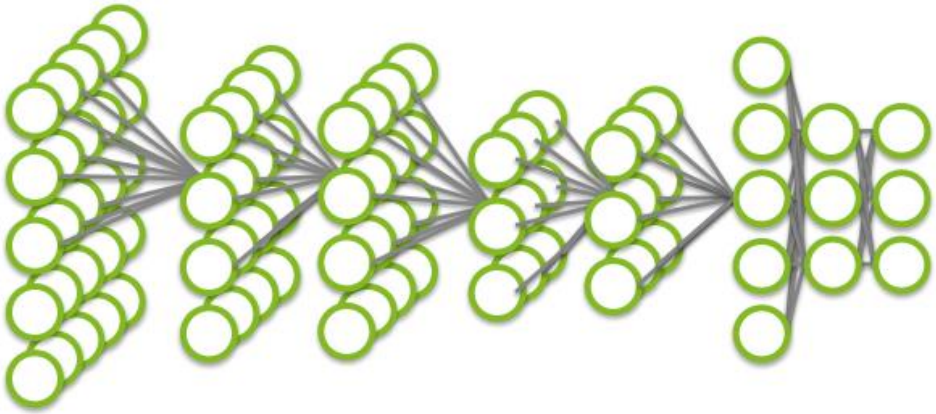
# Why Deep Learning?

- Hand engineering features for unstructured data is almost impossible!

Raw data

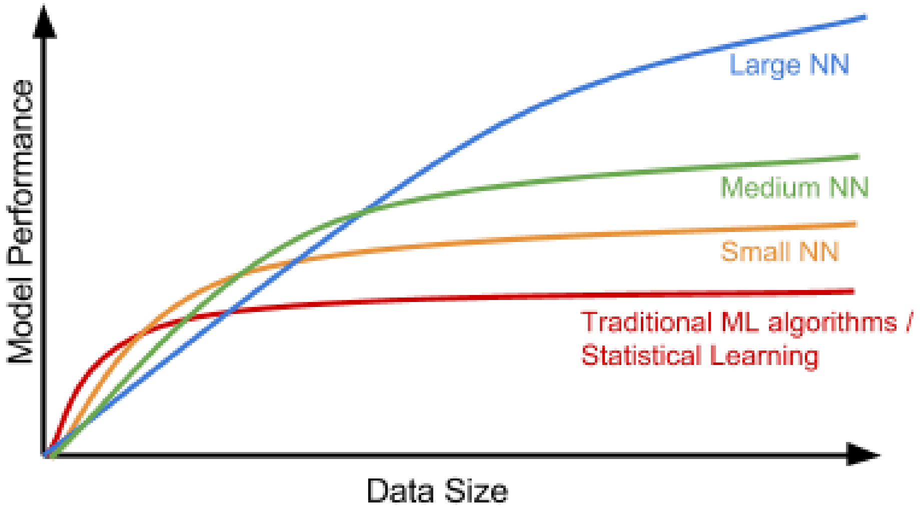



# Why Deep Learning?

| | **Machine Learning** | **Deep Learning** |
|---|---|---|
| Focus | General-purpose predictions | Extracting high-level features from data |
| Level of **Abstraction** | Explicitly programmed (rules/algos) | Learn by adjusting neurons |
| Examples | KNN, SVM, DT, RF, XGBoost, … | CNN, RNN, LSTM, GAN, Transformers |
| **Requires Feature extraction** | Yes | No |
| Requires high processing power | Not necessarily | Yes |
| Interpretability | Medium to low | Very low to none |
| Execution Time on training | Less (compared to DL) | A lot |
| Execution Time on testing | More (compared to DL) | Little |

# Why Now?

- In small data sets, perhaps traditional machine learning is more effective!
- The performance of deep learning is better when the data is large.
- Training large NN is computationally expensive.
- Algorithms are playing important role in speeding up the training process.

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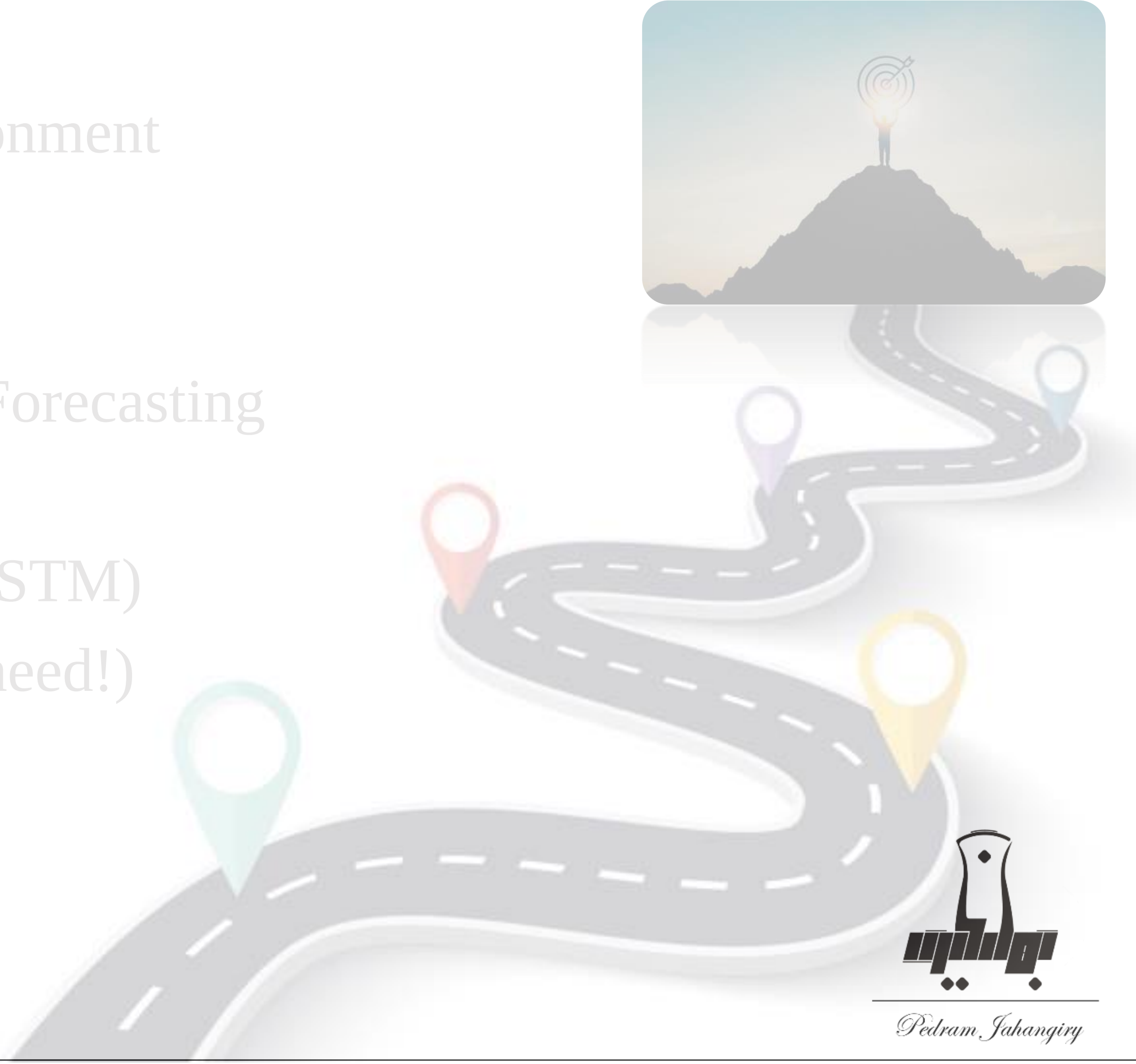

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