

Cheat Sheet – Bias-Variance Tradeoff

What is Bias?

- Error between average model prediction and ground truth
- The bias of the estimated function tells us the capacity of the underlying model to predict the values

$$\text{bias} = \mathbb{E}[f'(x)] - f(x)$$

What is Variance?

- Average variability in the model prediction for the given dataset
- The variance of the estimated function tells you how much the function can adjust to the change in the dataset

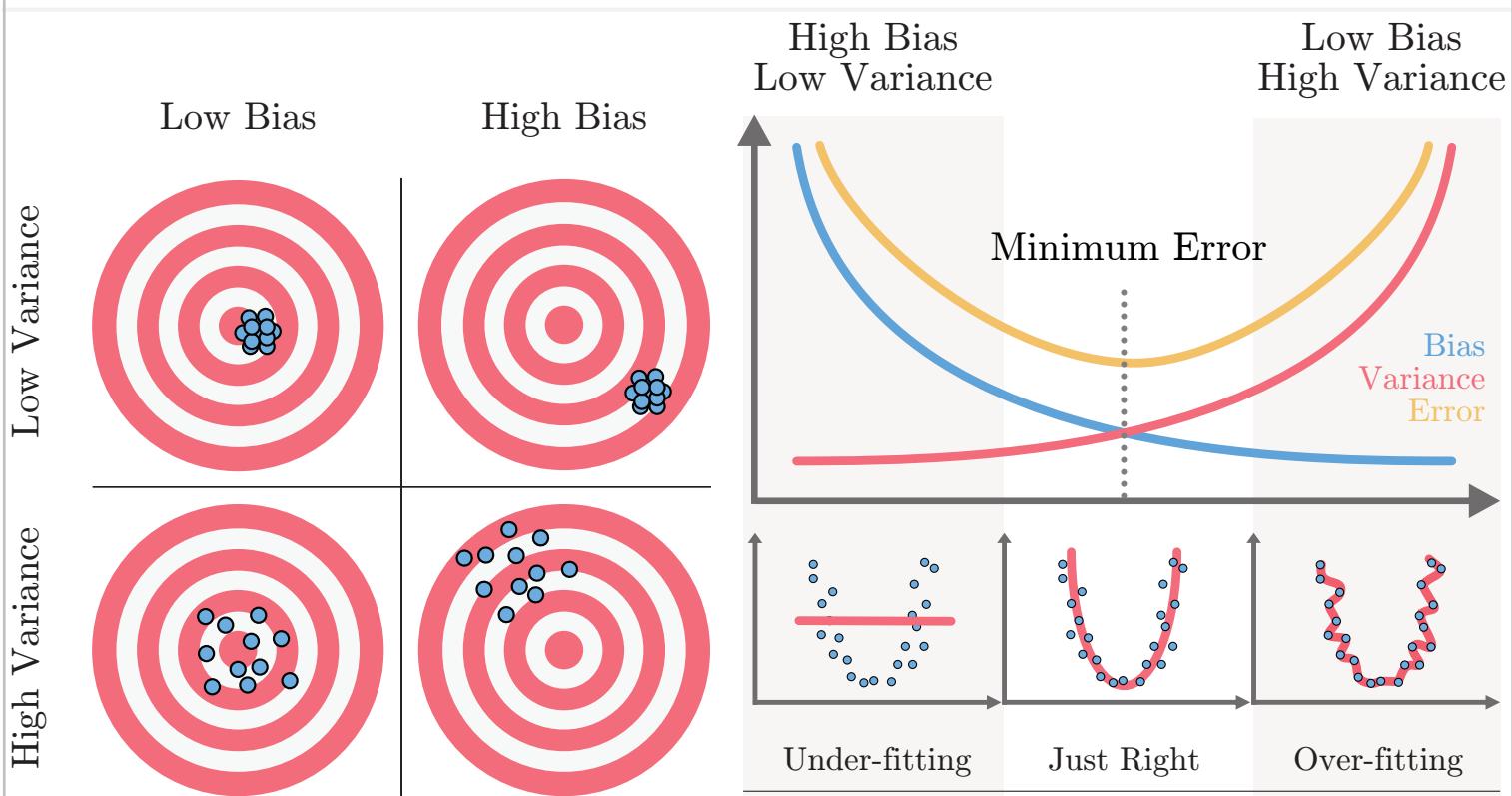
$$\text{variance} = \mathbb{E}[(f'(x) - \mathbb{E}[f'(x)])^2]$$

High Bias

- Overly-simplified Model
- Under-fitting
- High error on both test and train data

High Variance

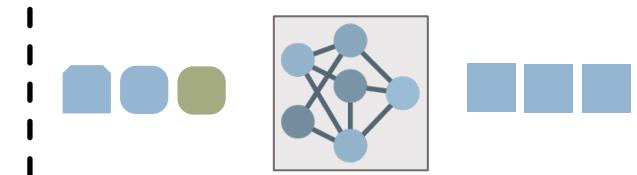
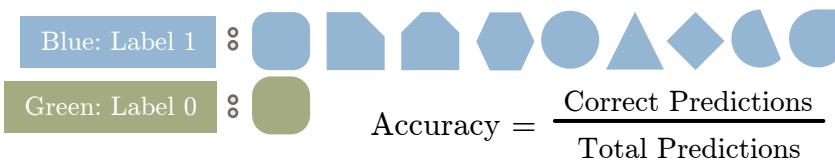
- Overly-complex Model
- Over-fitting
- Low error on train data and high on test
- Starts modelling the noise in the input



Bias variance Trade-off

- Increasing bias (not always) reduces variance and vice-versa
- Error = bias² + variance + irreducible error
- The best model is where the error is reduced.
- Compromise between bias and variance

Cheat Sheet – Imbalanced Data in Classification



Classifier that always **predicts label blue** yields prediction accuracy of 90%

Accuracy doesn't always give the correct insight about your trained model

Accuracy: %age correct prediction
Precision: Exactness of model

Correct prediction over total predictions
 From the detected cats, how many were actually cats

One value for entire network
 Each class/label has a value

Recall: Completeness of model
F1 Score: Combines Precision/Recall

Correctly detected cats over total cats
 Harmonic mean of Precision and Recall

Each class/label has a value
 Each class/label has a value

Performance metrics associated with Class 1

| | | Actual Labels | |
|------------------|---|----------------|----------------|
| | | 1 | 0 |
| Predicted Labels | 1 | True Positive | False Positive |
| | 0 | False Negative | True Negative |

(Is your prediction correct?) (What did you predict)

| | |
|--------------------------------------|---------------------------|
| True | Negative |
| (Your prediction is <u>correct</u>) | (You predicted <u>0</u>) |

Precision = $\frac{\text{TP}}{\text{TP} + \text{FP}}$

F1 score = $2x \frac{(\text{Prec} \times \text{Rec})}{(\text{Prec} + \text{Rec})}$

Specificity = $\frac{\text{TN}}{\text{TN} + \text{FP}}$

False +ve rate = $\frac{\text{FP}}{\text{TN} + \text{FP}}$

Accuracy = $\frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$

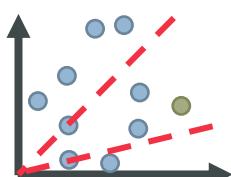
Recall, Sensitivity = $\frac{\text{TP}}{\text{TP} + \text{FN}}$
True +ve rate

Possible solutions

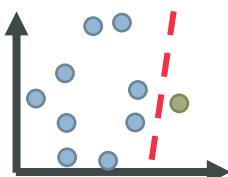
- Data Replication:** Replicate the available data until the number of samples are comparable
- Synthetic Data:** Images: Rotate, dilate, crop, add noise to existing input images and create new data
- Modified Loss:** Modify the loss to reflect greater error when misclassifying smaller sample set
- Change the algorithm:** Increase the model/algorithim complexity so that the two classes are perfectly separable (Con: Overfitting)



$$\text{loss} = a * \text{loss}_{\text{green}} + b * \text{loss}_{\text{blue}} \quad a > b$$



Increase model complexity



Straight line ($y=ax+b$) can perfectly separate data.
 Green class will no longer be predicted as blue

No straight line ($y=ax$) passing through origin can perfectly separate data. **Best solution:** line $y=0$, predict all labels blue

Cheat Sheet – PCA Dimensionality Reduction

What is PCA?

- Based on the dataset find a new set of orthogonal feature vectors in such a way that the data spread is maximum in the direction of the feature vector (or dimension)
- Rates the feature vector in the decreasing order of data spread (or variance)
- The datapoints have maximum variance in the first feature vector, and minimum variance in the last feature vector
- The variance of the datapoints in the direction of feature vector can be termed as a measure of information in that direction.

Steps

- Standardize the datapoints
- Find the covariance matrix from the given datapoints
- Carry out eigen-value decomposition of the covariance matrix
- Sort the eigenvalues and eigenvectors

$$X_{new} = \frac{X - \text{mean}(X)}{\text{std}(X)}$$

$$C[i, j] = \text{cov}(x_i, x_j)$$

$$C = V\Sigma V^{-1}$$

$$\Sigma_{sort} = \text{sort}(\Sigma) \quad V_{sort} = \text{sort}(V, \Sigma_{sort})$$

Dimensionality Reduction with PCA

- Keep the first m out of n feature vectors rated by PCA. These m vectors will be the best m vectors preserving the maximum information that could have been preserved with m vectors on the given dataset

Steps:

- Carry out steps 1-4 from above
- Keep first m feature vectors from the sorted eigenvector matrix $V_{reduced} = V[:, 0 : m]$
- Transform the data for the new basis (feature vectors) $X_{reduced} = X_{new} \times V_{reduced}$
- The importance of the feature vector is proportional to the magnitude of the eigen value

Figure 1

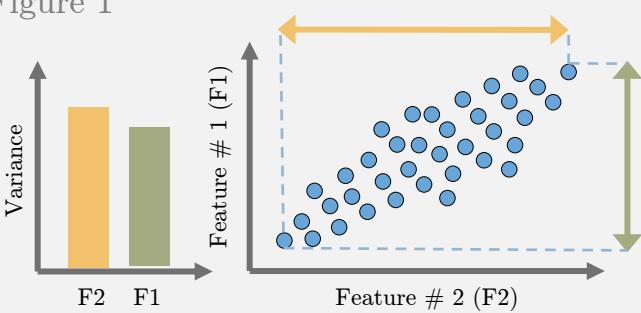


Figure 2

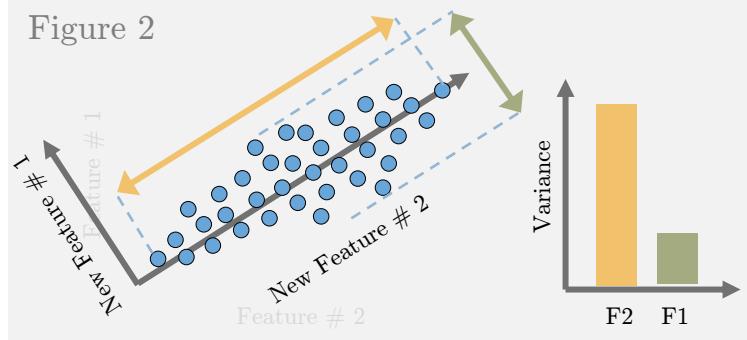


Figure 3

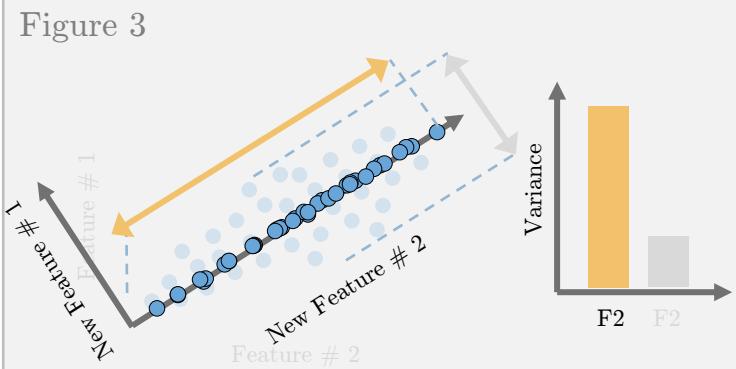


Figure 1: Datapoints with feature vectors as x and y-axis

Figure 2: The cartesian coordinate system is rotated to maximize the standard deviation along any one axis (new feature # 2)

Figure 3: Remove the feature vector with minimum standard deviation of datapoints (new feature # 1) and project the data on new feature # 2

Cheat Sheet – Bayes Theorem and Classifier

What is Bayes' Theorem?

- Describes the probability of an event, based on prior knowledge of conditions that might be related to the event.

$$P(A|B) = \frac{P(B|A)(\text{likelihood}) \times P(A)(\text{prior})}{P(B)(\text{evidence})}$$

- How the probability of an event changes when we have knowledge of another event

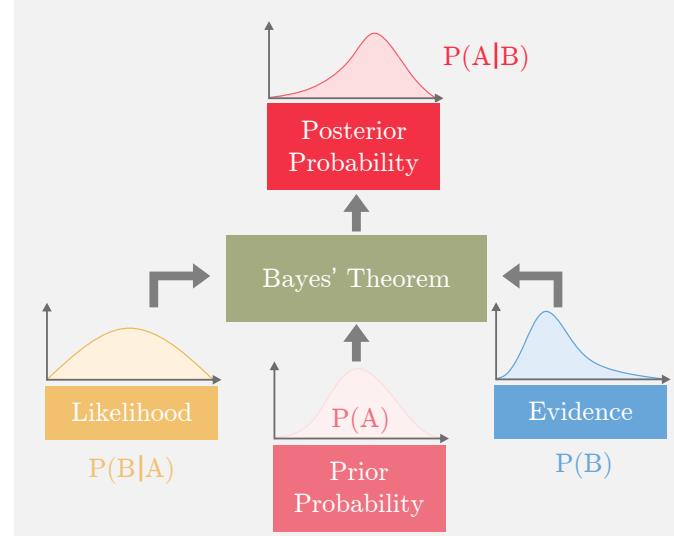
$$P(A) \longrightarrow P(A|B)$$

Usually, a better estimate than $P(A)$

Example

- Probability of fire $P(F) = 1\%$
- Probability of smoke $P(S) = 10\%$
- Prob of smoke given there is a fire $P(S|F) = 90\%$
- What is the probability that there is a fire given we see a smoke $P(F|S)?$

$$P(F|S) = \frac{P(S|F) \times P(F)}{P(S)} = \frac{0.9 \times 0.01}{0.1} = 9\%$$



Maximum Aposteriori Probability (MAP) Estimation

The MAP estimate of the random variable y , given that we have observed iid (x_1, x_2, x_3, \dots) , is given by. We try to accommodate our prior knowledge when estimating.

$$\hat{y}_{MAP} = \operatorname{argmax}_y P(y) \prod_i P(x_i|y)$$

y that maximizes the product of prior and likelihood

Maximum Likelihood Estimation (MLE)

The MAP estimate of the random variable y , given that we have observed iid (x_1, x_2, x_3, \dots) , is given by. We assume we don't have any prior knowledge of the quantity being estimated.

$$\hat{y}_{MLE} = \operatorname{argmax}_y \prod_i P(x_i|y)$$

y that maximizes only the likelihood

MLE is a special case of MAP where our prior is uniform (all values are equally likely)

Naïve Bayes' Classifier (Instantiation of MAP as classifier)

Suppose we have two classes, $y=y_1$ and $y=y_2$. Say we have more than one evidence/features (x_1, x_2, x_3, \dots) , using Bayes' theorem

$$P(y|x_1, x_2, x_3, \dots) = \frac{P(x_1, x_2, x_3, \dots | y) \times P(y)}{P(x_1, x_2, x_3, \dots)}$$

Naïve Bayes' theorem assumes the features (x_1, x_2, \dots) are i.i.d. i.e $P(x_1, x_2, x_3, \dots | y) = \prod_i P(x_i|y)$

$$P(y|x_1, x_2, x_3, \dots) = \prod_i P(x_i|y) \frac{P(y)}{P(x_1, x_2, x_3, \dots)}$$

$$\hat{y} = y_1 \text{ if } \frac{P(y_1|x_1, x_2, x_3, \dots)}{P(y_2|x_1, x_2, x_3, \dots)} > 1 \text{ else } \hat{y} = y_2$$

Cheat Sheet – Regression Analysis

What is Regression Analysis?

Fitting a function $f(\cdot)$ to datapoints $y_i = f(x_i)$ under some error function. Based on the estimated function and error, we have the following types of regression

1. Linear Regression:

Fits a **line** minimizing the **sum of mean-squared error** for each datapoint.

$$\min_{\beta} \sum_i \|y_i - f_{\beta}^{\text{linear}}(x_i)\|^2$$

$$f_{\beta}^{\text{linear}}(x_i) = \beta_0 + \beta_1 x_i$$

2. Polynomial Regression:

Fits a **polynomial** of order k ($k+1$ unknowns) minimizing the **sum of mean-squared error** for each datapoint.

$$\min_{\beta} \sum_{i=0}^m \|y_i - f_{\beta}^{\text{poly}}(x_i)\|^2$$

$$f_{\beta}^{\text{poly}}(x_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_k x_i^k$$

3. Bayesian Regression:

For each datapoint, fits a **gaussian distribution** by minimizing the **mean-squared error**. As the number of data points x_i increases, it converges to point estimates i.e. $n \rightarrow \infty, \sigma^2 \rightarrow 0$

$$\mathcal{N}(\mu, \sigma^2) \rightarrow \text{Gaussian with mean } \mu \text{ and variance } \sigma^2$$

4. Ridge Regression:

Can fit either a **line**, or **polynomial** minimizing the **sum of mean-squared error** for each datapoint **and** the **weighted L2 norm** of the function parameters beta.

$$\min_{\beta} \sum_{i=0}^m \|y_i - f_{\beta}(x_i)\|^2 + \sum_{j=0}^k \beta_j^2$$

$$f_{\beta}(x_i) = f_{\beta}^{\text{poly}}(x_i) \text{ or } f_{\beta}^{\text{linear}}(x_i)$$

5. LASSO Regression:

Can fit either a **line**, or **polynomial** minimizing the **sum of mean-squared error** for each datapoint **and** the **weighted L1 norm** of the function parameters beta.

$$\min_{\beta} \sum_{i=0}^m \|y_i - f_{\beta}(x_i)\|^2 + \sum_{j=0}^k |\beta_j|$$

$$f_{\beta}(x_i) = f_{\beta}^{\text{poly}}(x_i) \text{ or } f_{\beta}^{\text{linear}}(x_i)$$

6. Logistic Regression:

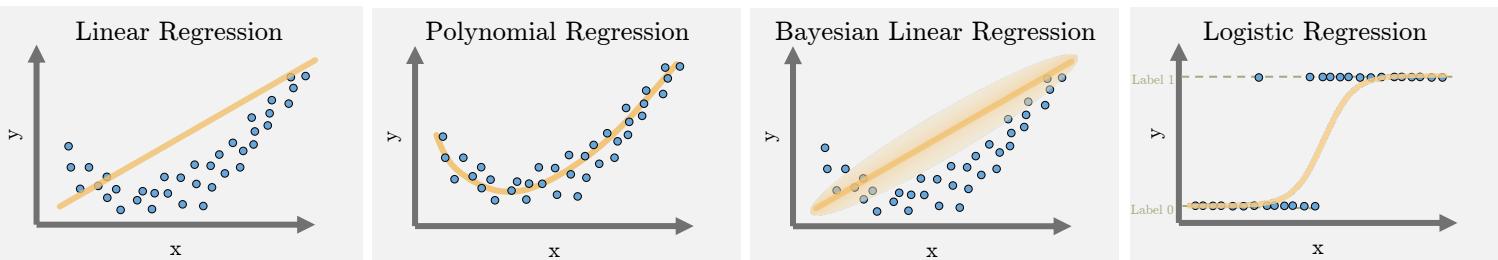
Can fit either a **line**, or **polynomial with sigmoid activation** minimizing the **binary cross-entropy loss** for each datapoint. The labels y are binary class labels.

$$\min_{\beta} \sum_i -y_i \log(\sigma(f_{\beta}(x_i))) - (1 - y_i) \log(1 - \sigma(f_{\beta}(x_i)))$$

$$f_{\beta}(x_i) = f_{\beta}^{\text{poly}}(x_i) \text{ or } f_{\beta}^{\text{linear}}(x_i)$$

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$

Visual Representation:



Summary:

| | What does it fit? | Estimated function | Error Function |
|-----------------|--------------------------------------|--|--|
| Linear | A line in n dimensions | $f_{\beta}^{\text{linear}}(x_i) = \beta_0 + \beta_1 x_i$ | $\sum_{i=0}^m \ y_i - f_{\beta}(x_i)\ ^2$ |
| Polynomial | A polynomial of order k | $f_{\beta}^{\text{poly}}(x_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots$ | $\sum_{i=0}^m \ y_i - f_{\beta}(x_i)\ ^2$ |
| Bayesian Linear | Gaussian distribution for each point | $\mathcal{N}(f_{\beta}(x_i), \sigma^2)$ | $\sum_i \ y_i - \mathcal{N}(f_{\beta}(x_i), \sigma^2)\ ^2$ |
| Ridge | Linear/polynomial | $f_{\beta}^{\text{poly}}(x_i) \text{ or } f_{\beta}^{\text{linear}}(x_i)$ | $\sum_{i=0}^m \ y_i - f_{\beta}(x_i)\ ^2 + \sum_{j=0}^n \beta_j^2$ |
| LASSO | Linear/polynomial | $f_{\beta}^{\text{poly}}(x_i) \text{ or } f_{\beta}^{\text{linear}}(x_i)$ | $\sum_{i=0}^m \ y_i - f_{\beta}(x_i)\ ^2 + \sum_{j=0}^n \beta_j $ |
| Logistic | Linear/polynomial with sigmoid | $\sigma(f_{\beta}(x_i))$ | $\min_{\beta} \sum_i -y_i \log(\sigma(f_{\beta}(x_i))) - (1 - y_i) \log(1 - \sigma(f_{\beta}(x_i)))$ |

Cheat Sheet – Regularization in ML

What is Regularization in ML?

- Regularization is an approach to address over-fitting in ML.
- Overfitted model fails to generalize estimations on test data
- When the underlying model to be learned is low bias/high variance, or when we have small amount of data, the estimated model is prone to over-fitting.
- Regularization reduces the variance of the model

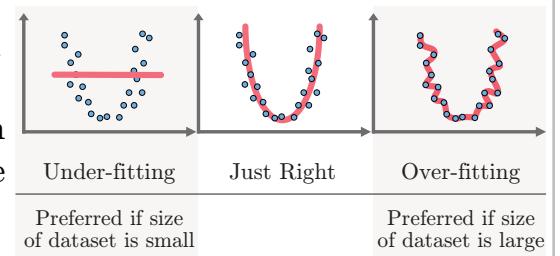


Figure 1. Overfitting

Types of Regularization:

1. Modify the loss function:

- **L2 Regularization:** Prevents the weights from getting too large (defined by L2 norm). Larger the weights, more complex the model is, more chances of overfitting.

$$\text{loss} = \text{error}(y, \hat{y}) + \lambda \sum_j \beta_j^2 \quad \lambda \geq 0, \lambda \propto \text{model bias}, \lambda \propto \frac{1}{\text{model variance}}$$

- **L1 Regularization:** Prevents the weights from getting too large (defined by L1 norm). Larger the weights, more complex the model is, more chances of overfitting. L1 regularization introduces sparsity in the weights. It forces more weights to be zero, than reducing the average magnitude of all weights

$$\text{loss} = \text{error}(y, \hat{y}) + \lambda \sum_j |\beta_j| \quad \lambda \geq 0, \lambda \propto \text{model bias}, \lambda \propto \frac{1}{\text{model variance}}$$

- **Entropy:** Used for the models that output probability. Forces the probability distribution towards uniform distribution.

$$\text{loss} = \text{error}(p, \hat{p}) - \lambda \sum_i \hat{p}_i \log(\hat{p}_i) \quad \lambda \geq 0, \lambda \propto \text{model bias}, \lambda \propto \frac{1}{\text{model variance}}$$

2. Modify data sampling:

- **Data augmentation:** Create more data from available data by randomly cropping, dilating, rotating, adding small amount of noise etc.
- **K-fold Cross-validation:** Divide the data into k groups. Train on (k-1) groups and test on 1 group. Try all k possible combinations.

3. Change training approach:

- **Injecting noise:** Add random noise to the weights when they are being learned. It pushes the model to be relatively insensitive to small variations in the weights, hence regularization
- **Dropout:** Generally used for neural networks. Connections between consecutive layers are randomly dropped based on a dropout-ratio and the remaining network is trained in the current iteration. In the next iteration, another set of random connections are dropped.

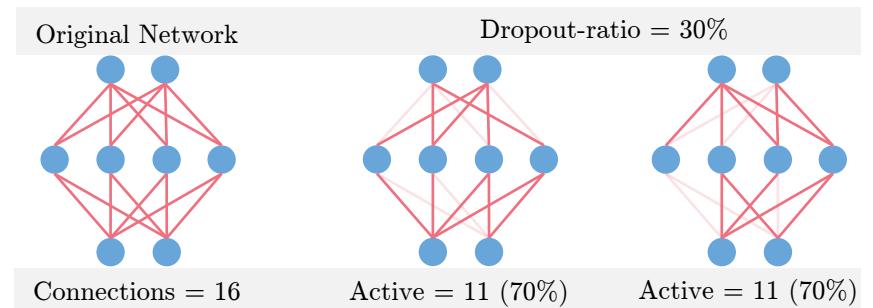
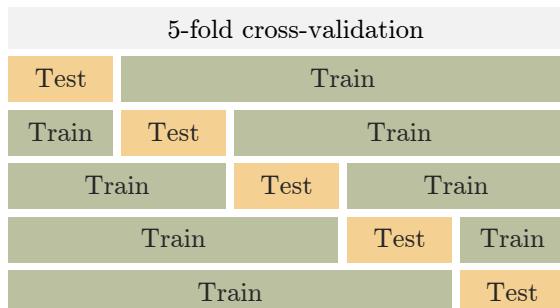


Figure 2. K-fold CV

Figure 3. Drop-out

Cheat Sheet – Convolutional Neural Network

Convolutional Neural Network:

The data gets into the CNN through the input layer and passes through various hidden layers before getting to the output layer. The output of the network is compared to the actual labels in terms of loss or error. The partial derivatives of this loss w.r.t the trainable weights are calculated, and the weights are updated through one of the various methods using backpropagation.

CNN Template:

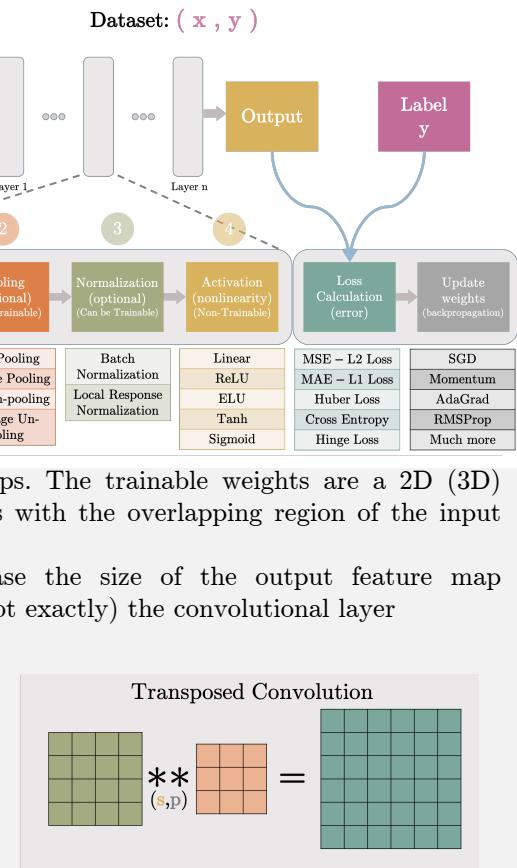
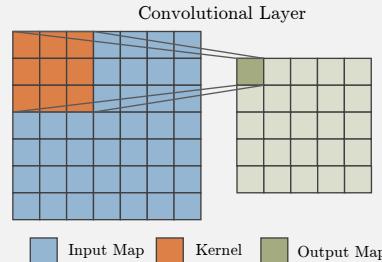
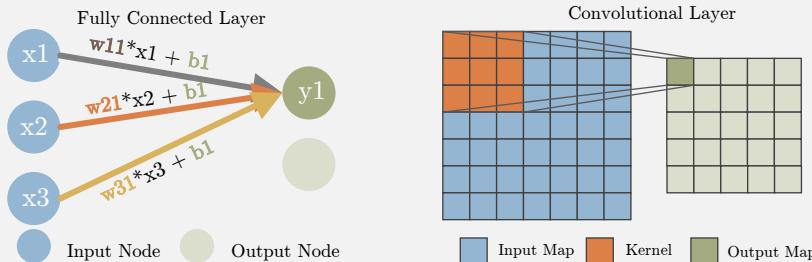
Most of the commonly used hidden layers (not all) follow a pattern

1. Layer function: Basic transforming function such as convolutional or fully connected layer.

a. Fully Connected: Linear functions between the input and the

a. Convolutional Layers: These layers are applied to 2D (3D) input feature maps. The trainable weights are a 2D (3D) kernel/filter that moves across the input feature map, generating dot products with the overlapping region of the input feature map.

b. Transposed Convolutional (DeConvolutional) Layer: Usually used to increase the size of the output feature map (Upsampling) The idea behind the transposed convolutional layer is to undo (not exactly) the convolutional layer



2. Pooling: Non-trainable layer to change the size of the feature map

a. Max/Average Pooling: Decrease the spatial size of the input layer based on selecting the maximum/average value in receptive field defined by the kernel

b. UnPooling: A non-trainable layer used to increase the spatial size of the input layer based on placing the input pixel at a certain index in the receptive field of the output defined by the kernel.

3. Normalization: Usually used just before the activation functions to limit the unbounded activation from increasing the output layer values too high

a. Local Response Normalization LRN: A **non-trainable layer** that square-normalizes the pixel values in a feature map within a local neighborhood.

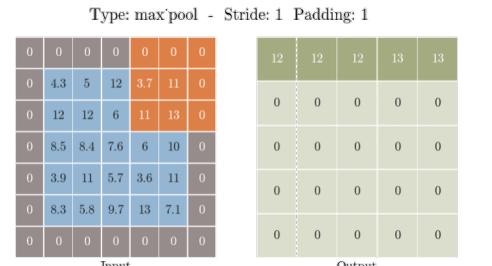
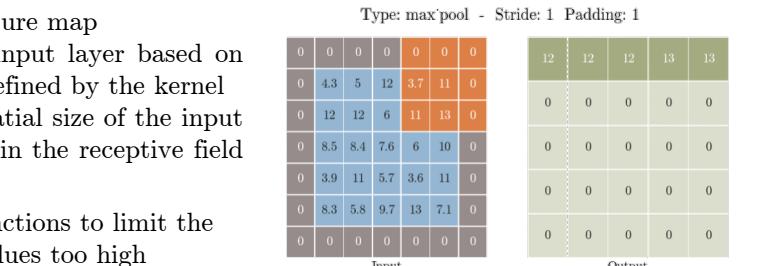
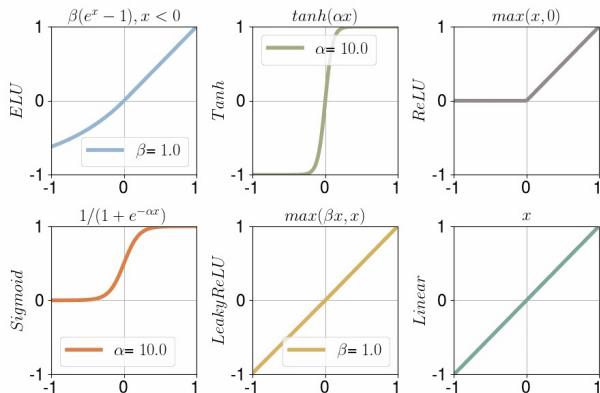
b. Batch Normalization: A trainable approach to normalizing the data by learning scale and shift variable during training.

3. Activation: Introduce non-linearity so CNN can efficiently map non-linear complex mapping.

a. Non-parametric/Static functions: Linear, ReLU

b. Parametric functions: ELU, tanh, sigmoid, Leaky ReLU

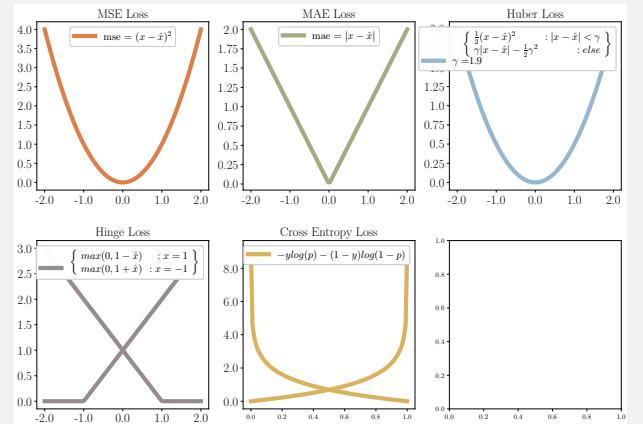
c. Bounded functions: tanh, sigmoid



5. Loss function: Quantifies how far off the CNN prediction is from the actual labels.

a. Regression Loss Functions: MAE, MSE, Huber loss

b. Classification Loss Functions: Cross entropy, Hinge loss



Cheat Sheet – Ensemble Learning in ML

What is Ensemble Learning? Wisdom of the crowd

Combine multiple weak models/learners into one predictive model to reduce bias, variance and/or improve accuracy.

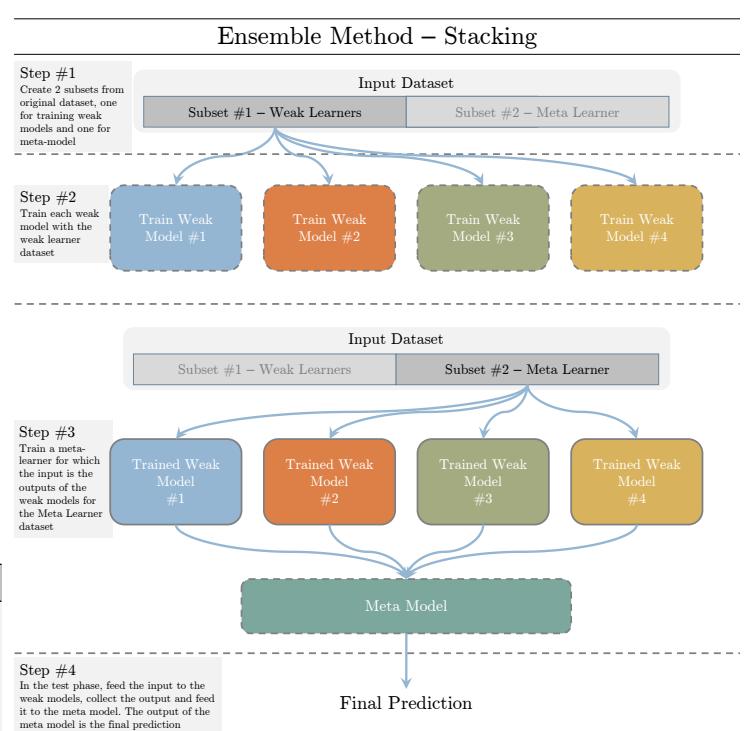
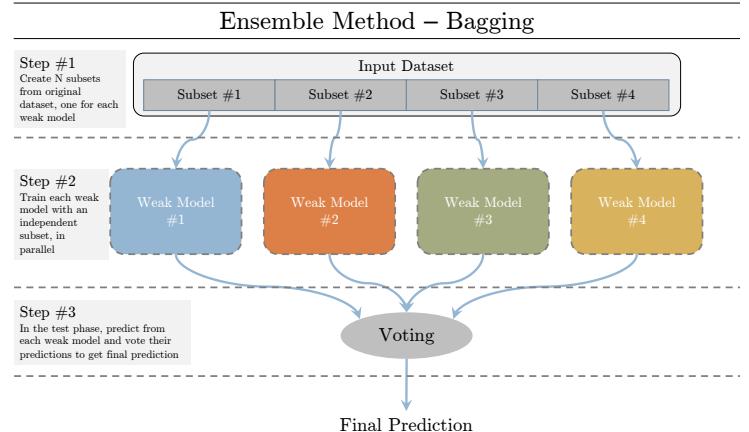
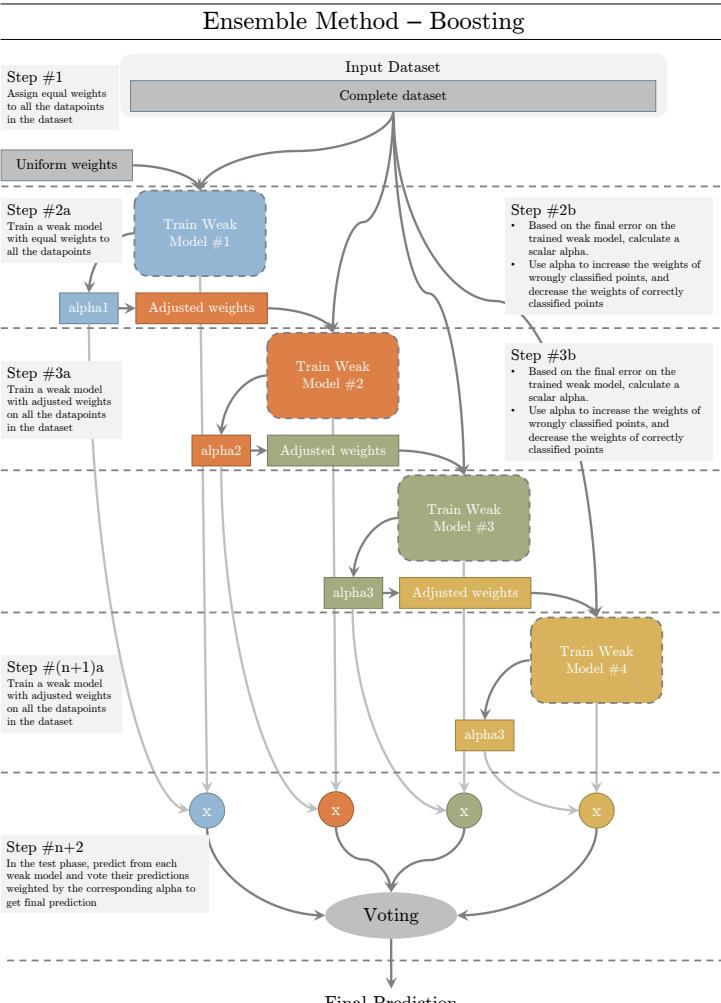
Types of Ensemble Learning: N number of weak learners

1.Bagging: Trains N different weak models (usually of same types – homogenous) with N non-overlapping subset of the input dataset in parallel. In the test phase, each model is evaluated. The label with the greatest number of predictions is selected as the prediction. Bagging methods reduces variance of the prediction

2.Boosting: Trains N different weak models (usually of same types – homogenous) with the complete dataset in a sequential order. The datapoints wrongly classified with previous weak model is provided more weights to that they can be classified by the next weak leaner properly. In the test phase, each model is evaluated and based on the test error of each weak model, the prediction is weighted for voting. Boosting methods decreases the bias of the prediction.

3.Stacking: Trains N different weak models (usually of different types – heterogenous) with one of the two subsets of the dataset in parallel. Once the weak learners are trained, they are used to trained a meta learner to combine their predictions and carry out final prediction using the other subset. In test phase, each model predicts its label, these set of labels are fed to the meta learner which generates the final prediction.

The block diagrams, and comparison table for each of these three methods can be seen below.



| Parameter | Bagging | Boosting | Stacking |
|---------------------------------|-------------------|-----------------|-------------------------------|
| Focuses on | Reducing variance | Reducing bias | Improving accuracy |
| Nature of weak learners is | Homogenous | Homogenous | Heterogenous |
| Weak learners are aggregated by | Simple voting | Weighted voting | Learned voting (meta-learner) |

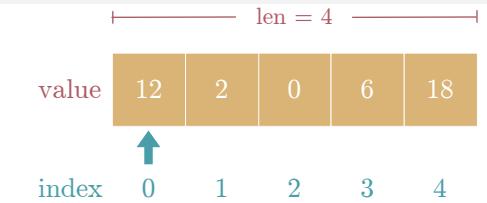
Cheat Sheet – Data Structures

1. List

- Ordered collection of elements
- The position of each element is defined by the *index*
- The elements can be accessed in *any order*



- Each linked list element contains both the values and the address (pointer) to the next linked list element.
- Hence the linked list can only be traversed sequentially going through each element at a time

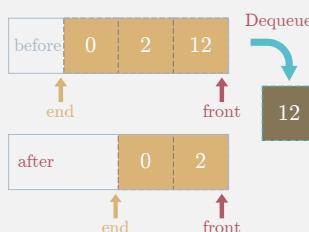
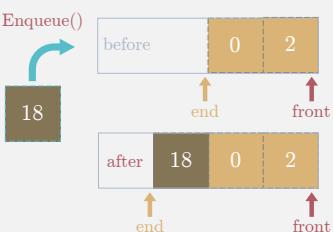
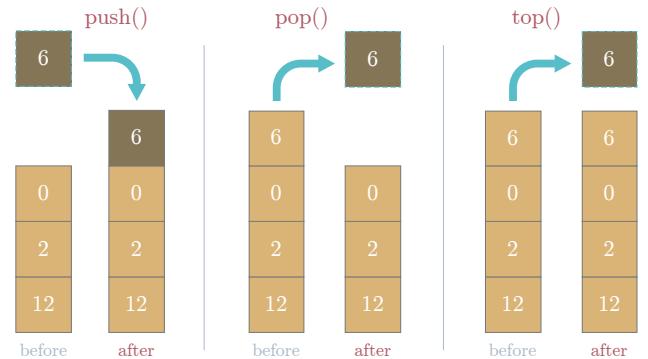


2. Linked List

- Linked List does not have their order defined by their physical placement in the memory.
- Contiguous elements of the linked list are not placed adjacent to each other in the memory.

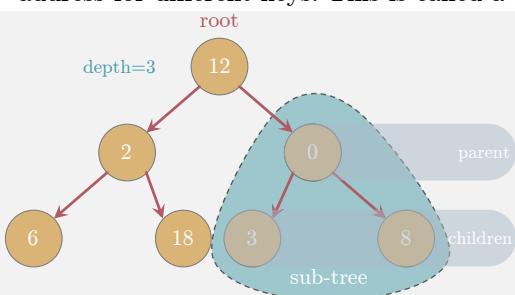
3. Stack

- Stack is a sequential data structure which maintains the order of elements as they were inserted in.
- Last In First Out (LIFO) order, which means that the elements can only be accessed in the reverse order as they were inserted into the stack.
- The element to be inserted last, will be the first one to get removed from the stack.
- Push()** adds an element at the head of the stack, while **pop()** removes an element from the head of the stack
- A real-life example of a stack is a stack of kitchen plates



5. HashTable

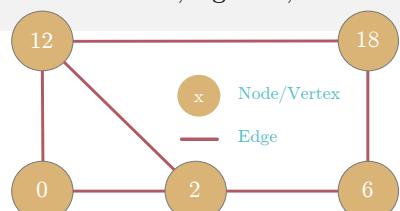
- Creates paired assignments (key mapped to values) so the pairs can be accessed in constant time
- For each (key, value) pair, the key is passed through a hash function to create a unique physical address for the value to be stored in the memory.
- Hash function can end up generating the same physical address for different keys. This is called a collision.



- Maintains a hierarchical relation between its elements.
- Root Node** – The node at the top of the tree
- Parent Node** – Any node that has at least one child
- Child Node** – The successor of a parent node is known as a child node. A node can be both a parent and a child node. The root is never a child node.
- Leaf Node** – The node which does not have any child node.
- Traversing** – Passing through the nodes in a certain order, e.g BFS, DFS

4. Graph

- A graph is a pair of sets (V, E), where V is set of all the vertices, E is set of all edges.
- A neighbor of a node is set of all vertices connected with that node through an edge.
- As opposed to trees, a graph can be cyclic, which means starting from a node and following the edges, you can end up on the same node



Cheat Sheet – Preparing for Coding Interviews

Part 1 – How to prepare for coding interviews?*

- The timeline:

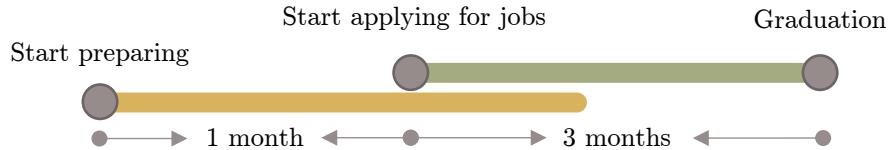


Fig. 1 – Preparation Timeline for Coding Interviews

- Review Data structures and Complexities:

The following 7 data structures are necessary for the interview, and their time/space complexity

- List/Arrays, Linked List, Hash Table/dictionary, Tree, Graph, Heap, Queue
- Click [here](#) for tutorial.

- Practice coding questions:

- Multiple online resources such as [LeetCode.com](#), [InterviewBit.com](#), [HackerRank.com](#) etc.
- Pick one online resource and aim for easy and medium coding questions (approx. 100-150).
- Beginners start preparing 2-3 months before the interview, and intermediates about 1 month.

- Note:

- From my personal experience, paid subscription of LeetCode.com was worth it.
- Facebook, Uber, Google and Microsoft tagged question of LeetCode covered almost 90% of the questions asked

Part 2 – How to answer a coding question?*

- Listen to the question

The interviewer will explain the question with an example. Note down the important points.

- Talk about your understanding of the question

Repeat the question and confirm your understanding. Ask clarifying questions such as

1. Input/Output data type limitations
2. Input size/length limitations
3. Special/Corner cases

- Discuss your approach

Walk through how would you approach the problem and ask the interviewer if he agrees with it.

Talk about the data structure you prefer and why. Discuss the solution with the bigger picture.

- Start coding

Ask the interviewer if you could start coding. Define useful functions and explain as you write.

Think out loud so the interviewer can evaluate your thought process.

- Discuss the time and space complexity

Discuss the time and space complexity in terms of Big O for your coded approach.

- Optimize the approach

If your approach is not the most optimized one, the interviewer will hint you a few improvements. Pay attention to hints and try to optimize your code.

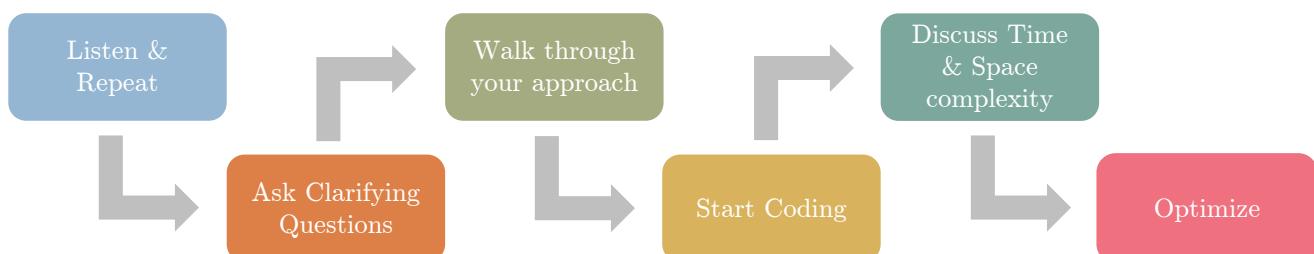


Fig. 2 – How to answer a coding question?

*Disclaimer: The recommendations are based on personal experiences of the author. The mentioned approach and resources might work great for some, but not so much for others.

1 /4

How to prepare for behavioral interview?

Collect stories, assign keywords, practice the STAR format



Keywords

List important keywords that will be populated with your personal stories. Most common keywords are given in the table below

| Conflict Resolution | Negotiation | Compromise to achieve goal | Creativity | Flexibility | Convincing |
|-----------------------|-------------------------------|-------------------------------------|-------------------------------------|-----------------------------|------------------------|
| Handling Crisis | Challenging Situation | Working with difficult people | Another team priorities not aligned | Adjust to a colleague style | Take Stand |
| Handling -ve feedback | Coworker view of you | Working with a deadline | Your strength | Your weakness | Influence Others |
| Handling failure | Handling unexpected situation | Converting challenge to opportunity | Decision without enough data | Conflict Resolution | Mentorship/ Leadership |

Stories

1. List all the organizations you have been a part of. For example
 1. Academia: BSc, MSc, PhD
 2. Industry: Jobs, Internship
 3. Societies: Cultural, Technical, Sports
2. Think of stories from step 1 that can fall into one of the keywords categories. The more stories the better. You should have at least 10-15 stories.
3. Create a summary table by assigning multiple keywords to each stories. This will help you filter out the stories when the question asked in the interview. An example can be seen below

| | |
|----------|---|
| Story 1: | [Convincing] [Take Stand] [influence other] |
| Story 2: | [Mentorship] [Leadership] |
| Story 3: | [Conflict resolution] [Negotiation] |
| Story 4: | [decision-without-enough-data] |

STAR Format

Write down the stories in the STAR format as explained in the 2/4 part of this cheat sheet. This will help you practice the organization of story in a meaningful way.

Icon Source: www.flaticon.com

2/4

How to prepare for behavioral interview?

Direct*, meaningful*, personalized*, logical*

(Respective colors are used to identify these characteristics in the example)



Example: "Tell us about a time when you had to convince senior executives"

Situation

Explain the situation and provide necessary context for your story.

S

"I worked as an intern in XYZ company in the summer of 2019. The project details provided to me was elaborative. After some initial brainstorming, and research I realized that the project approach can be modified to make it more efficient in terms of the underlying KPIs. I decided to talk to my manager about it."

Task

Explain the task and your responsibility in the situation

T

"I had an hour-long call with my manager and explained him in detail the proposed approach and how it could improve the KPIs. I was able to convince him. He asked me if I will be able to present my proposed approach for approval in front of the higher executives. I agreed to it. I was working out of the ABC(city) office and the executives need to fly in from XYZ(city) office."

Action

Walk through the steps and actions you took to address the issue

A

"I did a quick background check on the executives to know better about their area of expertise so that I can convince them accordingly. I prepared an elaborate 15 slide presentation starting with explaining their approach, moving onto my proposed approach and finally comparing them on preliminary results."

Result

State the outcome of the result of your actions

R

"After some active discussion we were able to establish that the proposed approach was better than the initial one. The executives proposed a few small changes to my approach and really appreciated my stand. At the end of my internship, I was selected among the 3 out of 68 interns who got to meet the senior vice president of the company over lunch."

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3/4

How to answer a behavioral question?

Understand, Extract, Map, Select and Apply



Example: "Tell us about a time when you had to convince senior executives"

Understand

Understand the question

Example: A story where I was able to convince my seniors. Maybe they had something in mind, and I had a better approach and tried to convince them

Extract

Extract keywords and tags

Extract useful keywords that encapsulates the gist of the question

Example:

[Convincing], [Creative], [Leadership]

Map

Map the keyword to your stories

Shortlist all the stories that fall under the keywords extracted from previous step

Example:

Story1, Story2, Story3, Story4, ... , Story N

Select

Select the best story

From the shortlisted stories, pick the one that best describes the question and has not been used so far in the interview

Example: Story3

Apply

Apply the STAR method

Apply the STAR method on the selected story to answer the question

Example: See Cheat Sheet 2/3 for details

Icon Source: www.flaticon.com

4/4

Behavioral Interview Cheat Sheet

Summarizing the behavioral interview



How to prepare for the interview

1

Gather important topics as keywords

Understand and collect all the important topics commonly asked in the interview

2

Collect your stories

Based on all the organizations you have been a part of, think of all the stories that fall under the keywords above

3

Practice stories in STAR format

Practice each story using the STAR format. You will have to answer the question following this format.

4

Assign keywords to stories

Assign each of your story one or more keywords. This will help you recall them quickly

5

Create a summary table

Create a summary table mapping stories to their associated keywords. This will be used during the behavioral question

How to answer a question during interview

U

Understand the question

Understand the question and clarify any confusions that you have

E

Extract the keywords

Try to extract one or more of the keywords from the question

M

Map the keywords to stories

Based on the keywords extracted, find the stories using the summary table created during preparation (Step 4)

S

Select a story

Since each keyword maybe assigned to multiple stories, select the one that is most relevant and has not been used.

A

Apply the START format

Once the story has been shortlisted, apply STAR format on the story to answer the question.

Icon Source: www.flaticon.com