### **Machine Learning Interviews**

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# Slides posted on Twitter @chipro

## My background

Writing



**Product** 

Cốc Cốc browser

20M+ monthly active users

Baomoi.com acquired by VNG

Youth Asia acquired by Groupon

AI/ML



### My work (very pro-OSS)



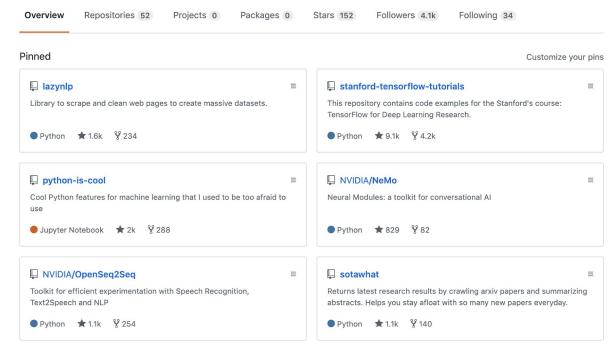
Chip Huyen chiphuyen

Edit profile

Deep Learning Algorithm @NVIDIA.

Taught "TensorFlow for Deep Learning
Research" @Stanford. Author of 3
bestselling books. Insta: huyenchip19

\*\*L\*\* @NVIDIA\*\*



#### **Contents**

- Machine learning jobs
- Getting a job in ML
- Understanding the interviewers' mindset
- Interview process
- Recruiting pipeline

## Machine learning jobs

 Research scientist vs research engineer Data scientist vs machine learning engineer

Research vs applied research

Research	Applied research
Find the answers for <b>fundamental</b> questions and expand the body of theoretical knowledge.	Find solutions to <b>practical</b> problems
Ex: develop a new learning method for unsupervised transfer learning	Ex: develop techniques to make that new learning method work on a real world dataset
Focus on long term outcome	Focus on <b>immediate</b> commercial outcome

#### **Caveats**

- Cutting-edge research is spearheaded by big corporations
- Lacking theories to explain methods that work well empirically

Research scientist	Research engineer
Develop original ideas	Use engineering to actualize these ideas
Might require PhDs	Don't require PhDs
Might act as an advisor to research engineers	Springboard to become research scientist

#### **Caveats**

- Depends on organizations/teams. In some teams, there are virtually no difference
- Scientists & engineers can be equal first authors (e.g. GPT-2, Transformer paper)

Data scientist	ML Engineers
Extract knowledge and insights from structured and unstructured data	ML models learn from data -> ML is part of data science
Use data to help company make decisions	Develop models to turn data into products
Is a scientist -> engineering isn't a top priority	Is an engineer -> engineering is a top priority

#### **Caveats**

 MLEs at startups might spend most of their time wrangling data, understanding data, setting up infrastructure, and deploying models instead of training ML models.

#### **Machine Learning Engineer (MLE)**

#### Umbrella term to cover:

- research engineer
- devrel engineer
- data scientist
- deep learning engineer
- generic machine learning engineer

#### It does not cover:

- ML DevOps
- framework engineer

ML at big companies

ML at startups

### **Big companies**

#### **Startups**

Can afford research

Can't (estimated cost of AlphaStar is \$26M)



Client: We'd like to do what big Al labs like OpenAl and

DeepMind are doing.

Me: You mean getting into a \$1B debt?

Client:

Me:

Client: So is there any free pretrained model that you

suggest that we use?

2:59 PM · Aug 7, 2019 · Twitter Web App

| View Tweet activity

101 Retweets 874 Likes

Big companies	Startups
Can afford research	Can't (estimated cost of AlphaStar is \$26M)
Can afford specialists	Need generalists

Big companies	Startups
Can afford research	Can't (estimated cost of AlphaStar is \$26M)
Can afford specialists	Need generalists
Standardized process	Make up process as they go

## Getting a job in ML

BS/MS in ML -> ML engineer
 Tech Ivies -> FAANG/startups

- 1. BS/MS in ML -> ML engineer
- 2. PhD in ML -> ML researcher
  Published at top-tier conferences -> FAANG/ML-first startups

- 1. BS/MS in ML -> ML engineer
- 2. PhD in ML -> ML researcher
- 3. Data scientist -> on-job training -> ML engineer/researcher Companies want to start using ML

- 1. BS/MS in ML -> ML engineer
- 2. PhD in ML -> ML researcher
- 3. Data scientist -> on-job training -> ML engineer/researcher
- 4. Software engineer -> courses -> ML engineer Software engineers want to transition into ML

- 1. BS/MS in ML -> ML engineer
- 2. PhD in ML -> ML researcher
- 3. Data scientist -> on-job training -> ML engineer/researcher
- 4. Software engineer -> courses -> ML engineer
- Adjacent fields -> on-job training -> ML researcher Not enough talents from Al/ML PhDs Ex: stats, physics, math

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- 5. Adjacent fields -> on-job training -> ML researcher
- 6. Unrelated fields -> residency/fellowship -> ML researcher Big companies: Google, Facebook, MSFT, NVIDIA, etc. Ex: health, art, architecture, agriculture

## Avoid anyone that promises you ML expertise in days or weeks!!

Senior role	Junior role
Hired for skills	Hired for attitude

#### Do you need a PhD?

interested in such as Google and Lyft might ignore my application due to not having an MS/PhD

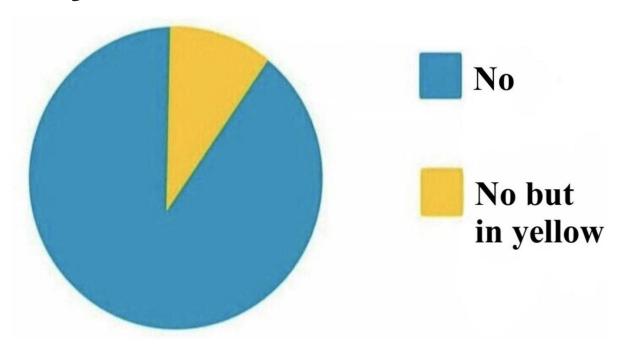
know fair amount of things in NLP and speech as well. Given that I don't have an MS/PhD, expertise in one field isn't taking me anywhere.

not required?

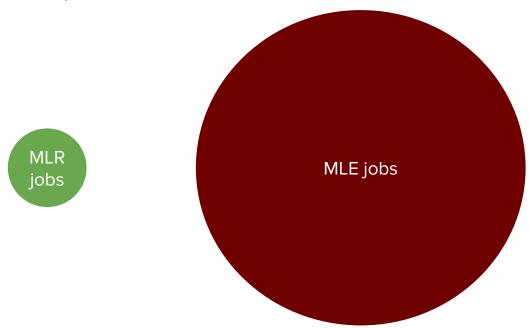
#### Do you need a PhD?

#### Detecting "Fake News" Before It is Even Written Dr. Preslav Nakov Principal Scientist. Qatar Computing Research Institute Panel Discussion: Al in Industry & Research Moderator: Dr. Thuc Vu - Co-founder & CEO, OhmniLabs & Kambria Panelists: Dr. James J. Kuffner - CEO of the Toyota Research Institute Advanced De Dr. Thang Luong - Research Scientist, Google Brain Huyen Chip - Senior Deep Learning, NVIDIA Dr. Hung Bui - Director, VinAl Research, VinGroup Dr. Preslav Nakov - Principal Scientist, Qatar Computing Research Institu Break / Coffee Machine Learning Interviews: Lessons from Both Sides Huyen Chip Senior Deep Learning Engineer, NVIDIA The Case for Al Research in Vietnam Dr. Hung Bui

## Do you need a PhD?



## The only role that might require a PhD is (applied) research scientist

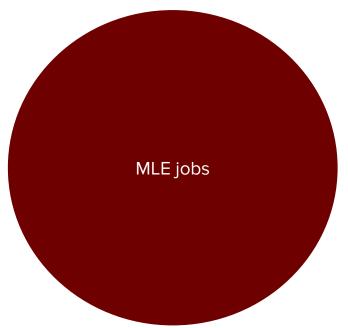


## The only role that might require a PhD is (applied) research scientist

#### We need more engineers:

- To improve research
- To productize research





# Understanding the interviewers' mindset

## 1. Companies hate hiring

- Expensive for companies
- Stressful for hiring managers
- Boring for interviewers

#### 2. Companies don't want the best people

They want the best people who can do <u>a reasonable job</u> within the <u>time and monetary constraints</u>.

## 3. Companies don't know what they're hiring for

They don't even know for sure if they'll need that person

-> job descriptions for reference purposes only

## 4. Most recruiters can't evaluate technical skills

They rely on weak signals:

- previous employers
- degrees
- awards/papers
- GitHub/Kaggle
- referrals

### Weak signals

- previous employers
- degrees
- awards/papers
- GitHub/Kaggle
- referrals



When screening resumes for machine learning engineer roles, which signal is the most important to you?

Comment for other signals.

School names	10%
GitHub/Kaggle	54%
Previous employers	22%
Referrals	15%

2,458 votes · Final results

12:07 AM · Sep 27, 2019 · Twitter Web App

### **PSA:** Past projects aren't meritocratic

- Not everyone can afford to contribute to OSS or do Kaggle competitions.
- Placing too much importance on voluntary activities punishes candidates from less privileged background.

#### 5. Most interviewers are bad

Little or no training for interviewers even at big companies

### 6. Interview outcome depends on many random variables

It is, in no way, a reflection of your ability or your self-worth

Evolved out of the traditional software engineering interview process

- 1. Resume screen
- 2. Phone screen
- 3. Coding challenges / take-home assignments
- 4. Technical offsite interviews (1 2)
- 5. Onsite interviews (4 8)

#### PSA:

Take-home assignments punish less privileged candidates!!

- 1. Resume screen
- 2. Phone screen
- 3. Coding challenges / take-home assignments
- 4. Technical offsite interviews (1 2)
- 5. Onsite interviews (4 8)

#### **Onsites are tiring**

10.00 - 11.00	Natalie Portman	Software Engineer	Coding question
11.00 - 11.45	Stephen Chow	Research Scientist	ML theory
11.45 - 13.00	Constance Wu	Engineering Manager	Meeting the team
13.00 - 14.30	Irrfan Khan	Research Engineer	ML implementation
14.30 - 15.00	Dave Chappelle	VP of Engineering	Behavioral questions

- Questions that ask for the retention of knowledge that can be easily looked up
  - "write down the equation for the Adam optimizer."

- 1. Questions that ask for the retention of knowledge that can be easily looked up
- 2. Questions that evaluate irrelevant skills "write a linked list."

- 1. Questions that ask for the retention of knowledge that can be easily looked up
- 2. Questions that evaluate irrelevant skills
- 3. Questions whose solutions rely on one single insight "take derivative of  $x^x$ ."

- Questions that ask for the retention of knowledge that can be easily looked up
- 2. Questions that evaluate irrelevant skills
- 3. Questions whose solutions rely on one single insight
- 4. Questions that try to evaluate multiple skills at once "explain PCA to your grandma."

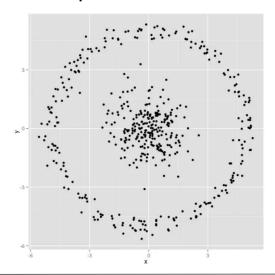
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- 5. Questions that use specific hard-to-remember names "Moore–Penrose inverse" or "Frobenius norm"

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- 6. Open-ended questions with one expected answer

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- 6. Open-ended questions with one expected answer
- 7. Easy questions during later interview rounds "find the longest common subsequence."

#### **Examples of good interview questions**

Given the following dataset, can you predict how K-means clustering works on it? Explain.



#### **Examples of good interview questions**

Imagine you have to train a NER model on the text corpus A. Would you make A case-sensitive or not?

#### **Examples of good interview questions**

Duolingo is a platform for language learning. When a student is learning a new language, Duolingo wants to recommend increasingly difficult stories to read.

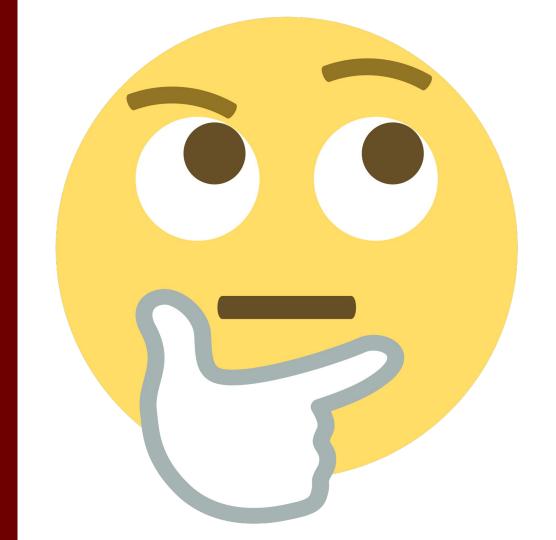
- 1. How would you measure the difficulty level of a story?
- 2. Given a story, how would you edit it to make it easier or more difficult?

#### **Alternative interview formats**

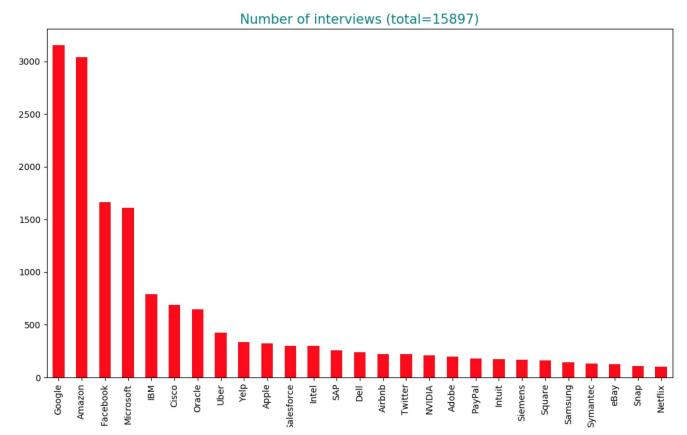
- Multiple choice quiz
- Quiz
- Code debugging
- Pair programming
- Good cop, bad cop

### Recruiting pipeline

- 1. ONSITE-TO-OFFER RATIO
- 2. OFFER YIELD RATE



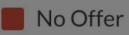
- **15,897** Glassdoor interview reviews
- **27** major tech companies

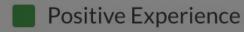


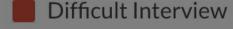


#### **Software Engineer Interview**

Anonymous Interview Candidate







#### **Application**



I applied through a recruiter. The process took 2+ months. I interviewed at Google in June 2014.

#### **Interview**

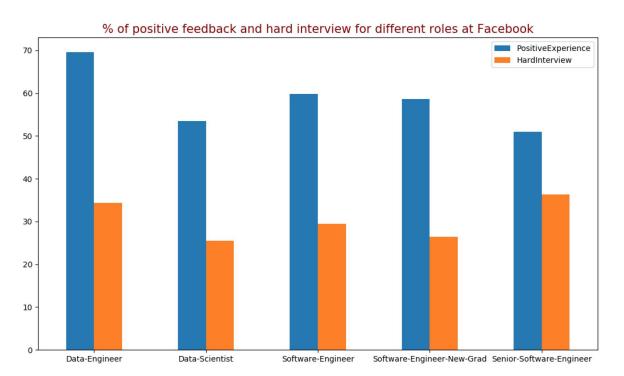


Was approached by a recruiter, we had an initial phone screen. From there, I had a technical phone interview with a SWE. The questions were pretty straight forward, nothing too difficult. After that, I had four on-site interviews. Two of them went very well, one went pretty well, and I did pretty poorly in the other. I signed an NDA, so I can't go into details, but my suggestion to...

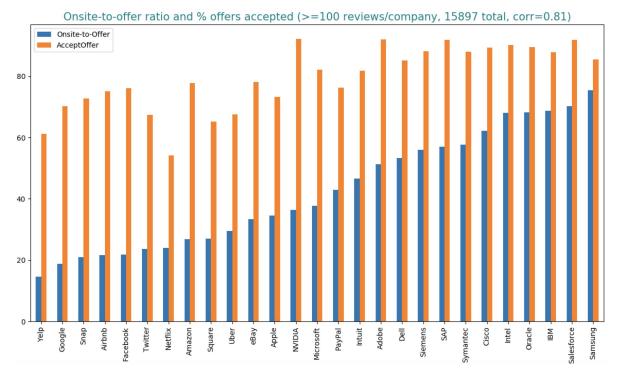
#### **Biases**

- few people leave reviews for anything online
- reviews are likely compelled by either a really good or really bad experience
- those who receive offers are more likely to give reviews than those who don't
- those who accept offers are more likely to give reviews than those who decline
- ...

# Interview feedback varies wildly even within the same company

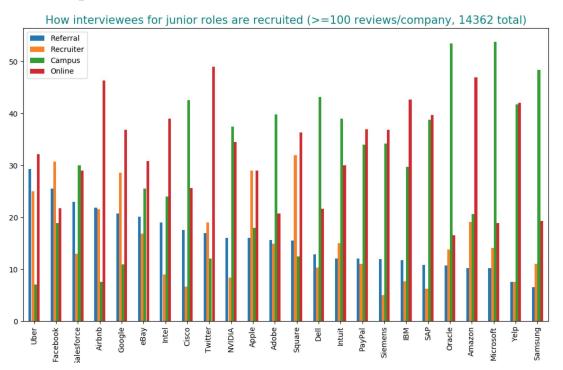


# The higher the onsite-to-offer ratio, the more likely offers are accepted



Link to blog post

# Most junior roles are sourced through campus or referrals



#### How important are referrals?

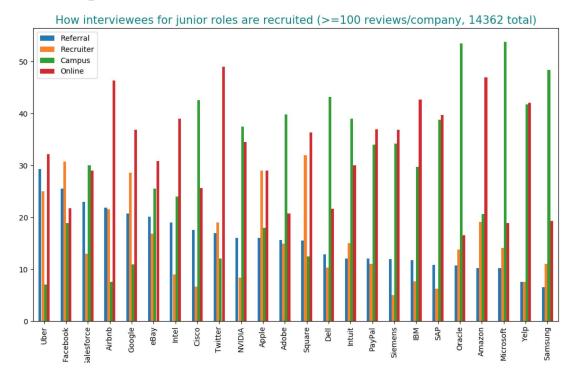
"By at least a 10x margin, the best candidate sources I've ever seen are friends and friends of friends."

- Sam Altman (Y Combinator)

"Referral quality was incredibly important – the 8 worst hires ... were all unknown to me and everyone at the company at the time of hiring."

- Lukas Biewald (Figure 8, Weights & Biases)

### Most junior roles are sourced through campus or referrals



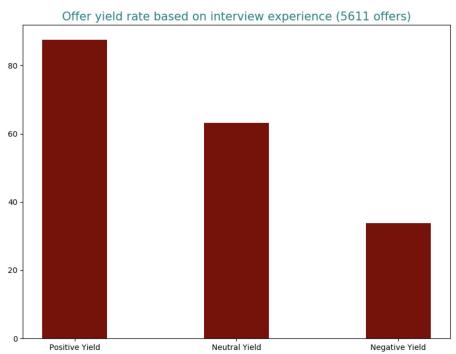
Tech Ivy mixer alert!!!

# school or know people who can refer you?

What if you don't go to a fancy engineering

- "Be so good they can't ignore you"
  - Steve Martin

# Candidates with negative experience are less likely to accept offers



#### **General tips**

- 1. Job search and interview preparation are lifelong processes.
- 2. The best time to interview is when you don't need a job.
- 3. Start looking for jobs 3-6 months before.
- 4. Build up your portfolio and publish them.
- 5. Get people to refer you.
- 6. Look up your interviewers. Review their work.
- 7. Have your friends to give you mock interviews.
- 8. Don't pretend that you know something when you don't.
- 9. Don't criticize your previous or current employers.
- 10. Don't talk about your age, marital status, religion, political affiliation.
- 11. Have competing offers.
- 12. Don't sweat it. If you tank an interview, move on.



I'm working on a book on machine learning interviews so I've been spending the last few months talking to companies about their hiring process for ML roles. This thread is a summary of what I've learned. It will be updated as the book progresses. (1/n)



#### Book info:

huyenchip.com/2019/07/21/machine-learning-interviews.html

### Thank you!

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