On How to Learn, Do and Write Theory

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How Theory is (Often) Taught

How Theory is (Often) Taught

- 1. Here is **problem X**.
- 2. Here is **method A**.
- 3. Therefore **solution**

How to Solve Theory Problems (?)

- 1. Write down the **problem X**.
- 2. Think *real* hard.
- 3. Write down the **solution**.

≈Murray Gell-Mann





How Theory is Done

Simplification







How Theory Problems are Solved

- 1. Isolate a toy **model case x** of major **problem X**.
- 2. Solve **model case x** using **method A**.
- 3. Try using **method A** to solve the full **problem X**.
- 4. This does not succeed but **method A** can be extended to **model cases x' and x''**.
- 5. Eventually, it is realized that **method A** relies crucially on a **property P** being true which holds for **model cases x, x' and x''**.
- 6. Conjecture that **property P** is true for all instances of **problem X**.
- 7. Discover a family f **counterexamples y, y', y''**,... to this conjecture.
- 8. Take the simplest **counterexample y** in this family, and try to solve **problem X** for this special case. Meanwhile, try to see whether **method A** can work without **property P**
- 9. Discover several counterexamples in which **method A** fails, in which the cause of failure can be definitely traced back to **property P**. Abandon efforts to modify **method A**.
- 10. Realize that **counterexample y** is related to a **problem Z** in another field.

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22. Method Z is rapidly developed and extended to get the solution to problem X.



How to Learn Theory

How to Learn Theory Simplification



Simplify theorems

- ignore lower order parameters / technical details
 - fix parameters
 - apply theorem to special cases

How to Learn Theory Simplification

Overview	skip nla
Plausible Markov Bound	pra ľ
Key Setup	
Standard Definitions	d
Cute Telescoping Probability	sp

Proof on Arbitrary Graphs

p standard + usible details

note tricks

lo proof on pecial cases



Proof on Regular Graphs

Simplify proofs

	$d(w_i, \{u, v\}) \le d(w_{i+1}, \{u, v\})$
for all i	-(-*)(-) = -(-*)(-) = -(-*)(-)
Now let's fix some Then by the defini Thus if <i>any</i> of thes at least one of u, v is a random permu Thus $\mathbf{Pr}[S_{iw_j} = 1]$ lemma.	w_j , and suppose that w_j cuts $\{u, v\}$ at level <i>i</i> , i.e., $ B(w_j, r_{i-1}) \cap \{u, v\} = 1$. tion of our ordering, every w_k with $k < j$ must have $ B(w_k, r_{i-1}) \cap \{u, v\} > 0$. e nodes come before w_j in π , we know that w_j will not settle u, v at level <i>i</i> , since will have already been clustered by the time w_j gets to form clusters. Since π itation, the probability that w_j comes before the x_k for all $k < j$ is exactly $1/j$. $X_{iw_j} = 1] \leq 1/j$. So by setting $b_{w_j} = 1/j$, we have proved the first part of the
	5
The proof of the se	econd part of the lemma is now straightforward:
*	n n r
	$\sum_{w \in V} b_w = \sum_{j=1}^{n} b_{w_j} = \sum_{j=1}^{n} \frac{1}{j} = H_n = O(\log n),$
as claimed.	$\sum_{w \in V} b_w = \sum_{j=1}^{n} b_{w_j} = \sum_{j=1}^{n} \frac{1}{j} = H_n = O(\log n),$
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Recreate Proofs after you learn them; see where you get stuck





Invent Stories that you like / will remember

Do the Same for LC Expander Decompositions?



why assumptions needed?



Theorem: Every planar graph is 4-colorable



what does this give on e.g.s?

Ask Yourself Questions









How does this

help me solve

my problem?





 \bigcirc



Maybe just a

Chernoff bound?



Ask Questions if you're confused









Ask Questions if you're confused



Just a Chernoff bound	



Ask Questions if you're confused

How to Learn Theory What to Aim For

Roadmaps of proof

Tools and stories you'll remember









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(up to constants)

Doing Theory is Hard

Can Succeed with a Wide Range of Aptitudes:

- Good memory
- Good
- Reliab
 Work to Your Strengths
- Just really curious
- Stick-To-Itiveness 🙀

• . . .





• Impatient / only interested in elegant solutions 爹

Theorem: Every tree is 4-colorable

You Will Get Stuck



Simplify your problem



You Will Get Stuck

STOC 2021

- Gharan (University of Washington).
- (University of Oxford), and Rahul Savani (University of Liverpool).
- Sahai (University of California at Los Angeles).

STOC 2020

• "Improved Bounds for The Sunflower Lemma", by Ryan Alweiss, Shachar Lovett, Kewen Wu, and Jiapeng Zhang.

STOC 2019

- "Oracle Separation of BPQ and PH", by Ran Raz and Avishay Tal.

STOC 2018

• "A Constant-Factor Approximation Algorithm for the Asymmetric Traveling Salesman Problem", by Ola Svensson, Jakub Tarnawski, and Lászaló A. Végh.

STOC 2017

- "Explicit, Almost Optimal, Epsilon-Balanced Codes", by Amnon Ta-Shma.
- "A Weighted Linear Matroid Parity Algorithm", by Satoru Iwata and Yusuke Kobayashi.

STOC 2016

- "Explicit Two-Source Extractors and Resilient Functions", by Eshan Chattopadhyay and David Zuckerman
- "Graph Isomorphism in Quasipolynomial Time", by László Babai.

OC 2015

- "Exponential Separation of Information and Communication for Boolean Functions", by Anat Ganor, Gillat Kol, and Ran Raz.
- "2-Server PIR with Sub-Polynomial Communication", by Zeev Dvir and Sivakanth Gopi.

Collaborations

You Will Get Stuck

🖌 * "A (Slightly) Improved Approximation Algorithm for Metric TSP", by Anna R. Karlin (University of Washington), Nathan Klein (University of Washington), and Shayan Oveis

• "The Complexity of Gradient Descent: CLS = PPAD \cap PLS", by John Fearnley (University of Liverpool), Paul W. Goldberg (University of Oxford), Alexandros Hollender

"Indistinguishability Obfuscation from Well-Founded Assumptions", by Aayush Jain (University of California at Los Angeles), Huijia Lin (University of Washington), and Amit

"Log-Concave Polynomials II: High-Dimensional Walks and an FPRAS for Counting Basis of a Matroid", by Nima Anari, Kuikui Liu, Shayan Oveis Gharan, and Cynthia Vinza "The Reachability Problem for Petri Nets Is Not Elementary", by Wojciech Czerwiński, Sławomir Lasota, Ranko Lazić, Jérôme Leroux, and Filip Mazowiecki.

"Deciding Parity Games in Quasipolynomial Time", by Cristian Calude, Sanjay Jain, Bakhadyr Khoussainov, Wei Li, and Frank Stephan.

"Reed-Muller Codes Achieve Capacity on Erasure Channels", by Shrinivas Kudekar, Santhosh Kumar, Marco Mondelli, Henry D. Pfister, Eren Sasoglu, and Rudiger Urbanke.

"Lower Bounds on the Size of Semidefinite Programming Relaxations", by James Lee, Prasad Raghavendra, and David Steurer.

STOC Best Papers

Collaborate





You Will Get Stuck

Read Related Work





You Will Get Stuck



Cut Yourself Slack

How to Do Theory **A Few Mantras**

Didn't result in a paper



My Time in Grad School

Failure is Common



Didn't result in a paper



My Time in Grad School

Learning is Progress

But resulted in knowledge

which resulted in another **problem**

which resulted in a collaboration

several years later

which resulted in a paper



How to Do Theory **A Few Mantras**



How Theory Problems are Solved

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- 6. Conjecture that **property** P is true for all instances of **problem X**.
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- 8. Take the simplest **counterexample y** in this family, and try to solve **problem X** for this special case. Meanwhile, try to see whether **method A** can work without **property P**
- 9. Discover several counterexamples in which **method A** fails, in which the cause of failure can be definitely traced back to property P. Abandon efforts to modify method A.
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Any New Insight is Progress



How to Do Theory **A Few Mantras**



Learn to Love the Process Not the Outcome



How to Write Theory

Writing Dos and Don'ts **Bad References**

Proof:

Theorem 1: 1+1+1=3

First we show 1+1=2...

Next, we show 2+1=3...

Theorem 2: 2+1+1=4

Proof:

First we show 1+1=2...

Next, we show 2+2=4...

Abstract out reused arguments into lemmas



Theorem 1: 1+1+1=3

Proof:

By Lemma 1+1=2

Next, we show 2+1=3...

Theorem 2: 2+1+1=4

Proof:

By Lemma 1+1=2

Next, we show 2+2=4...

Writing Dos and Don'ts **Bad References**

Proof:

Theorem 1: 1+1+1=3

First we show 1+1=2...

Next, we show 2+1=3...

Theorem 2: 2+1+1=4

Proof:

By the argument in Theorem 1, 1+1=2 Next, we show 2+2=4...

Don't reference the insides of other proofs



Theorem 1: 1+1+1=3

Proof:

By Lemma 1+1=2...

Next, we show 2+1=3...

Theorem 2: 2+1+1=4

Proof:

By Lemma 1+1=2...

Next, we show 2+2=4...

Writing Dos and Don'ts **Bad References**



Proof:

Hershkowitz et al. showed that 1+1=2...

Next, we show 2+1=3...

Don't reference facts not stated as theorems/lemmas/etc.



Lemma[Hershkowitz et al.]: 1+1=2

Theorem 1: 1+1+1=3

Proof:

By Lemma 1+1=2...

Next, we show 2+1=3...

Writing Dos and Don'ts Intuition



Give intuition / an overview at the beginning of your proofs

Writing Dos and Don'ts Intuition





Balance intuition and formality





Just Right

Excruciating Formality

Writing Dos and Don'ts **General Style**

 $\operatorname{App}(A_S^{(i)}) \leq \tilde{O}(n^{1+O(\epsilon)} + N^{O(\epsilon)}L^2)$ Thus, and so $\sum_{S,i} \sum_{k} |\operatorname{supp}(A_{Si,k} \cup B_{Si,k})| \leq \sum_{k}$ plugging this bound on $\sum_{S,i,k} |\text{supp}(A_{Si,k} \cup B_{Si,k})|$ into the guarantees of Theorem 10.4 and the fact that our pairs are $L \cdot N^{O(\epsilon)}$ -batchable, we have that each time we compute a cutmatch in step 2, the total number of edges we add across all G_S for $S \in \mathcal{N}[h']$ for a fixed h' is at most $\tilde{O}(m+L)$ $N^{O(\epsilon)} + n^{1+O(\epsilon)} + N^{O(\epsilon)}L) = \tilde{O}(m + n^{1+O(\epsilon)} + L^2 \cdot N^{O(\epsilon)})$. Since we have $1/\epsilon$ iterations, it follows that the number of edges across all G_S for $S \in \mathcal{N}[h']$ is never more than $\frac{1}{\epsilon} \cdot \tilde{O}(m + n^{1+O(\epsilon)} + L^2 \cdot N^{O(\epsilon)})$ It follows that the work and depth to compute all cut strategies for all $S \in \mathcal{N}[h']$ for all $1/\epsilon$ -many iterations and all $h' \leq h \cdot \frac{1}{\epsilon} \cdot (s)^{O(1/\epsilon)}$ a power of 2 in step 2 are respectively $\frac{1}{\epsilon} \cdot \sum_{i} W_{\text{cut-strat}}(A_i, m_i)$ and $\frac{1}{\epsilon} \cdot \max_i \mathsf{D}_{\text{cut-strat}}(A_i, m_i)$ where $|A_i| \leq |A|/L$ for all i and $\sum_i m_i \leq \tilde{O}(m + n^{1+O(\epsilon)} + L^2 \cdot N^{O(\epsilon)})$

Use whitespace (align*s) generously

and so

$$\sum_{S,i} \sum_{k} |\operatorname{supp}(A_{Si,k} \cup B_{Si,k})| \le \sum_{S,i} N^{O_{i}} \operatorname{supp}(A_{S}^{(i)}) \le \tilde{O}(n^{1+O(\epsilon)} + N^{O(\epsilon)}L^{2})$$

Thus, plugging this bound on $\sum_{S,i,k} |\operatorname{supp}(A_{Si,k} \cup B_{Si,k})|$ into the guarantees of Theorem 10.4 and the fact that our pairs are $L \cdot N^{O(\epsilon)}$ -batchable, we have that each time we compute a cutmatch in step 2, the total number of edges we add across all G_S for $S \in \mathcal{N}[h']$ for a fixed h' is at most

$$\tilde{O}(m+L\cdot N^{O(\epsilon)}+n^{1+O(\epsilon)}+N^{O(\epsilon)}L)=\tilde{O}(m+n^{1+O(\epsilon)}+L^2\cdot N^{O(\epsilon)}).$$

Since we have $1/\epsilon$ iterations, it follows that the number of edges across all G_S for $S \in \mathcal{N}[h']$ is never more than

$$\frac{1}{\epsilon} \cdot \tilde{O}(m + n^{1 + O(\epsilon)} + L^2 \cdot N^{O(\epsilon)})$$

It follows that the work and depth to compute all cut strategies for all $S \in \mathcal{N}[h']$ for all $1/\epsilon$ -many iterations and all $h' \leq h \cdot \frac{1}{\epsilon} \cdot (s)^{O(1/\epsilon)}$ a power of 2 in step 2 are respectively

$$\cdot \sum_{i} \mathsf{W}_{\text{cut-strat}}(A_i, m_i)$$
 (19)

and

$$\frac{1}{\epsilon} \cdot \max_{i} \mathsf{D}_{\text{cut-strat}}(A_i, m_i) \tag{20}$$

where $|A_i| \leq |A|/L$ for all *i* and $\sum m_i \leq \tilde{O}(m+n^{1+O(\epsilon)}+L^2 \cdot N^{O(\epsilon)})$

Writing Dos and Don'ts **General Style**



- 1. Vertices: Let $V_E := \{w_e, w'_e\}_{e \in E}$ be a set of vertices, two for each edge of *E*. The vertex set of our *k*-ECSM instance is $W := V \cup V_E$.
- 2. **Edges:** For each edge $e = \{u, v\} \in E$, we have 4 edges in our *k*-ECSM instance, namely $\{u, w_e\}, \{w_e, v\}, \{u, w'_e\}, \text{ and } \{w'_e, v\}$. Let E_{Gadget} be all such edges. The edge set of our *k*-ECSM instance is $B \coloneqq E_{\text{Gadget}} \cup L$.
- 3. **Costs:** The cost of each edge $b \in B$ in our *k*-ECSM instance is 1, i.e., $c_b = 1$.



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Use (a lot of) figures





Quoth the Raven "Nevermore".

Quoth the Raven "Nevermore".



Quoth the Raven ``Nevermore".

Quoth the Raven "Nevermore".





Inner product \$<x,y>\$.

Inner product $\langle x, y \rangle$.



Inner product **\$\langle** x,y **\rangle**\$.

Inner product $\langle x, y \rangle$.





\$(\frac{x^2}{y}) \leq z\$

$$\left(\frac{x^2}{y}\right) \leq z$$



$frac{x^2}y}$

$$\left(\frac{x^2}{y}\right) \leq z$$





 $ALG(x) = \log n$

ALG(x) = logn



$\textsc{ALG}(x) = \log n$

 $ALG(x) = \log n$





Let G be a k-connected graph.

Let G be a k-connected graph.

Let **\$**G**\$** be a **\$**k**\$**-connected graph.

Let G be a k-connected graph.



\begin{align}\label{eq} A & \leq B \\ & \leq D \end{align} so \$A \leq C\$ by \ref{eq}.

We have

$$\begin{array}{l} A \leq B \\ \leq C \end{array} \tag{1}$$

so $A \leq C$ by Equation 1.

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We have

$$A \le B$$
$$\le C$$

so $A \leq C$ by Equation 1.





\begin{proof}
\begin{align}
 A & \leq B \\
 & \leq D
\end{align}
\end{proof}

Proof.

 $\begin{aligned} A &\leq B \\ &\leq D. \end{aligned}$

\begin{proof} **We have** \begin{align} A & \leq B \\ & \leq D **\qedhere** \end{align} \end{proof}



 $\begin{aligned} A &\leq B \\ &\leq D. \end{aligned}$







Math is fun, e.g. algebra.

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Learning



Simplification











Infinite learning opportunities of beautiful facts



It's a **young** field (less to get up to speed with)



~2000 Years Ago



~100 Years Ago







Uniquely at the intersection of the **creative** and the **formal**

and (sometimes) the pra ti n 0







Theory +

- 1. guided by arcane laws

" "Music is the only **magic** left in this world." -Bob Dylan " -My dad

2. results often defy common sense 3. takes intense study to master