

Supercharging Jobs Marketplace: Optimizing Hiring Outcomes, Unified Jobs Marketplace, Big Auctions and Beyond

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YAHOO!
RESEARCH

Etsy

Linked 



Agenda

- 1 Optimizing Hiring Outcomes – (2020-2022)
- 2 Unified Jobs Marketplace – (2022-2023/24)
- 3 Big Auction and Beyond – (2023/24 – Today)



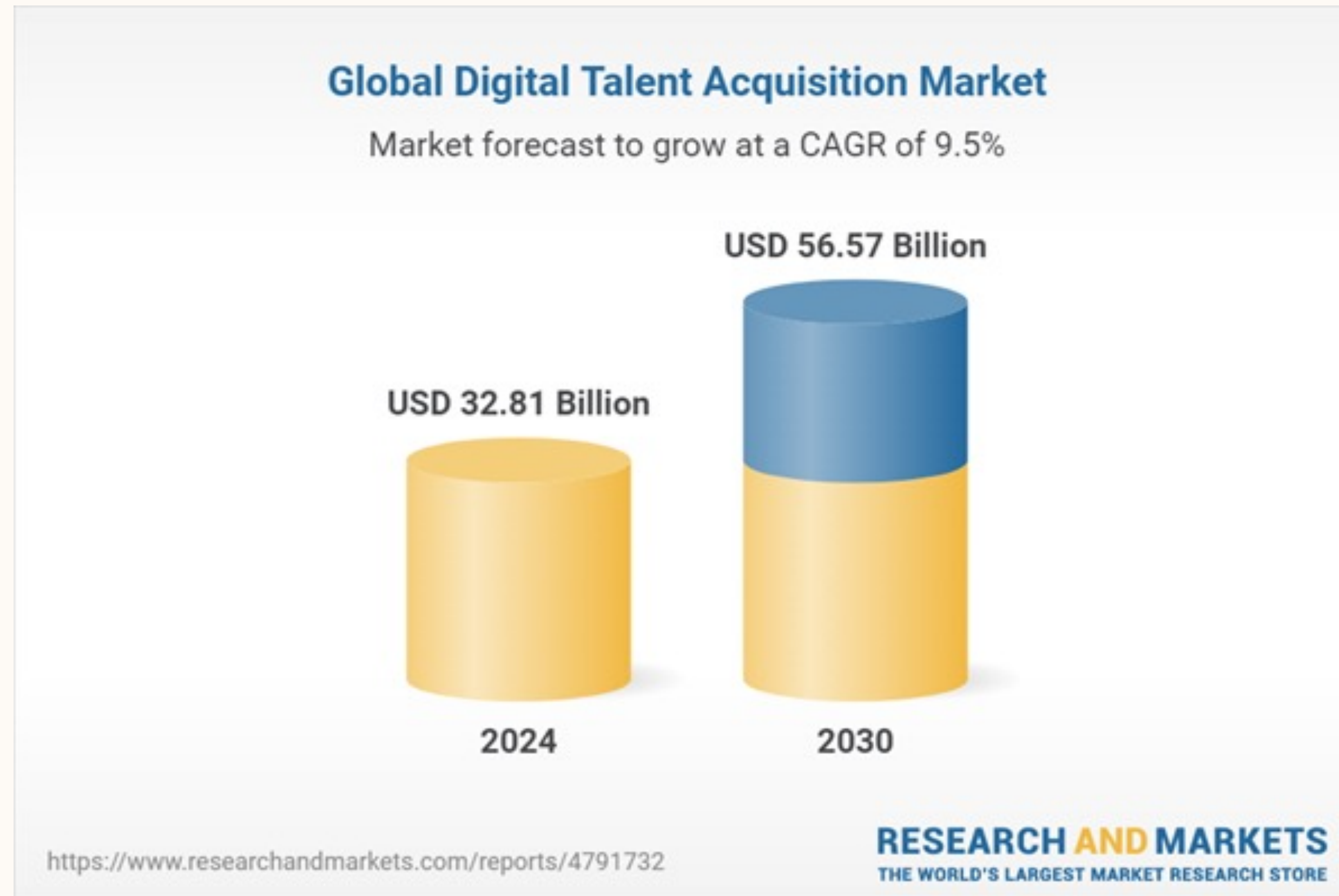
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- 2 Unified Jobs Marketplace – (2022-2023/24)**
- 3 Big Auction and Beyond – (2023/24 – Today)**

Online Jobs Marketplace: Job Market and Economy



Online Jobs Marketplace: The Global Trend



The Global Digital Talent Acquisition Market was estimated at USD 30.01 billion in 2023, USD 32.81 billion in 2024, and is expected to grow at a 9.47% to reach USD 56.57 billion by 2030.

Online Jobs Marketplace: Overall Ecosystem



Online Jobs Marketplace: Overall Ecosystem



Every second on LinkedIn...



100

Job Applications

submitted by LinkedIn members



21

InMails Sent

with job opportunities



0.1

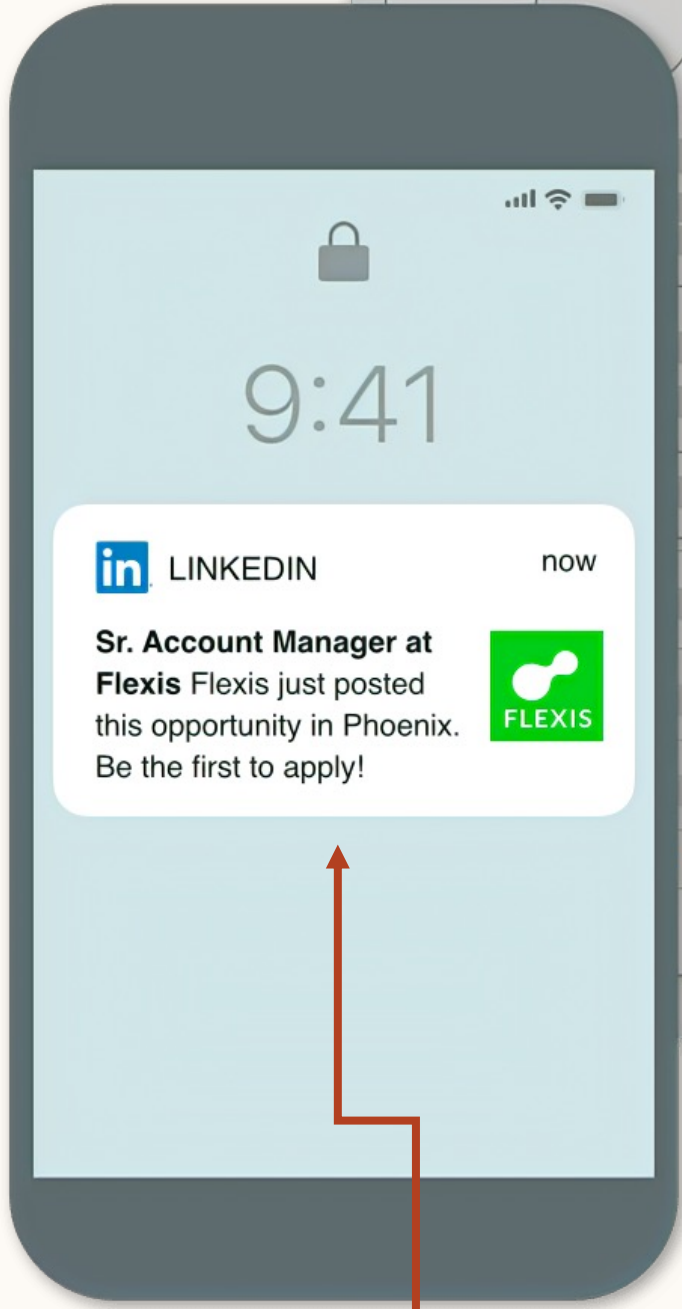
Hires

on LinkedIn

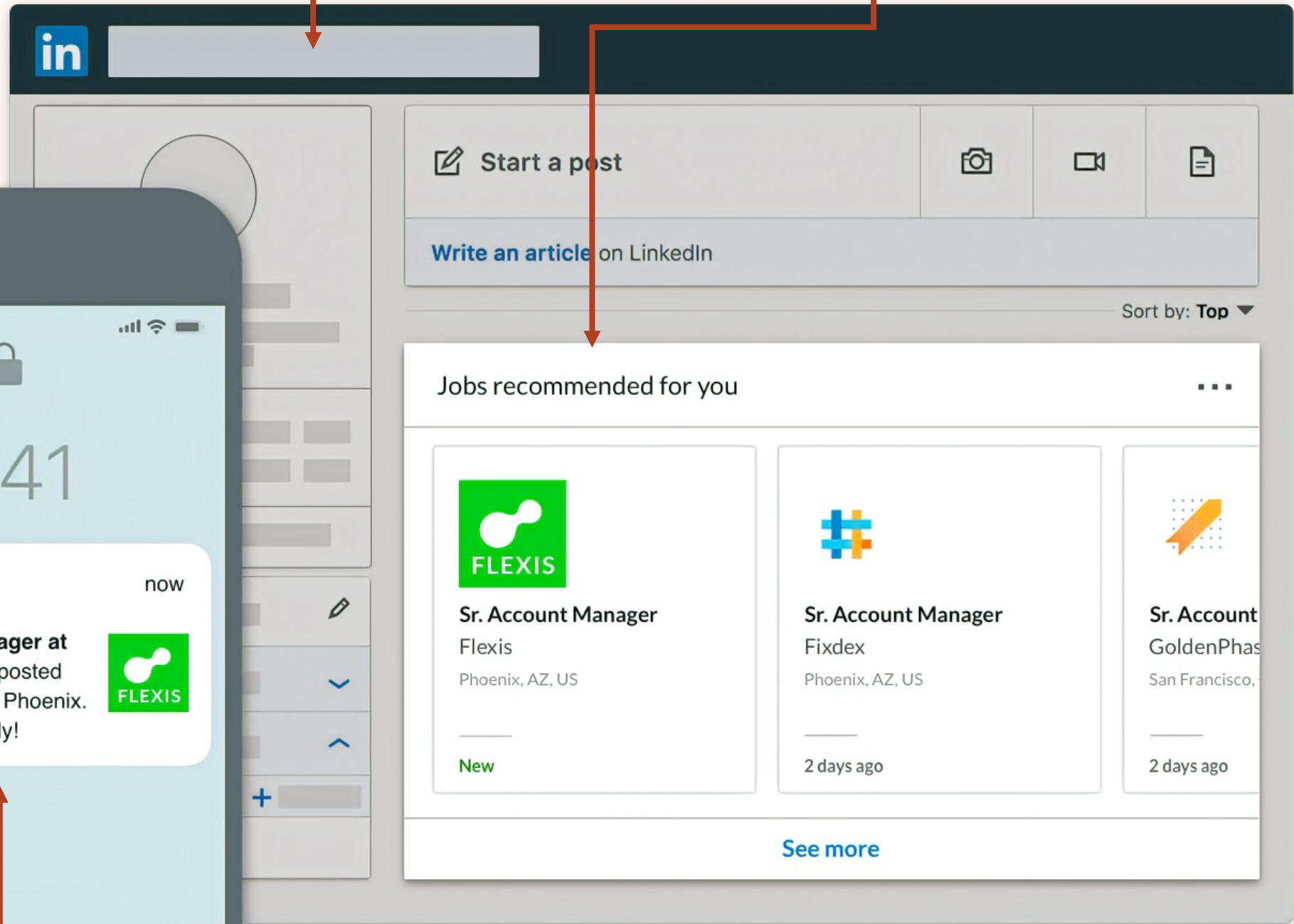
Job seekers

Search for jobs

Job recommendations



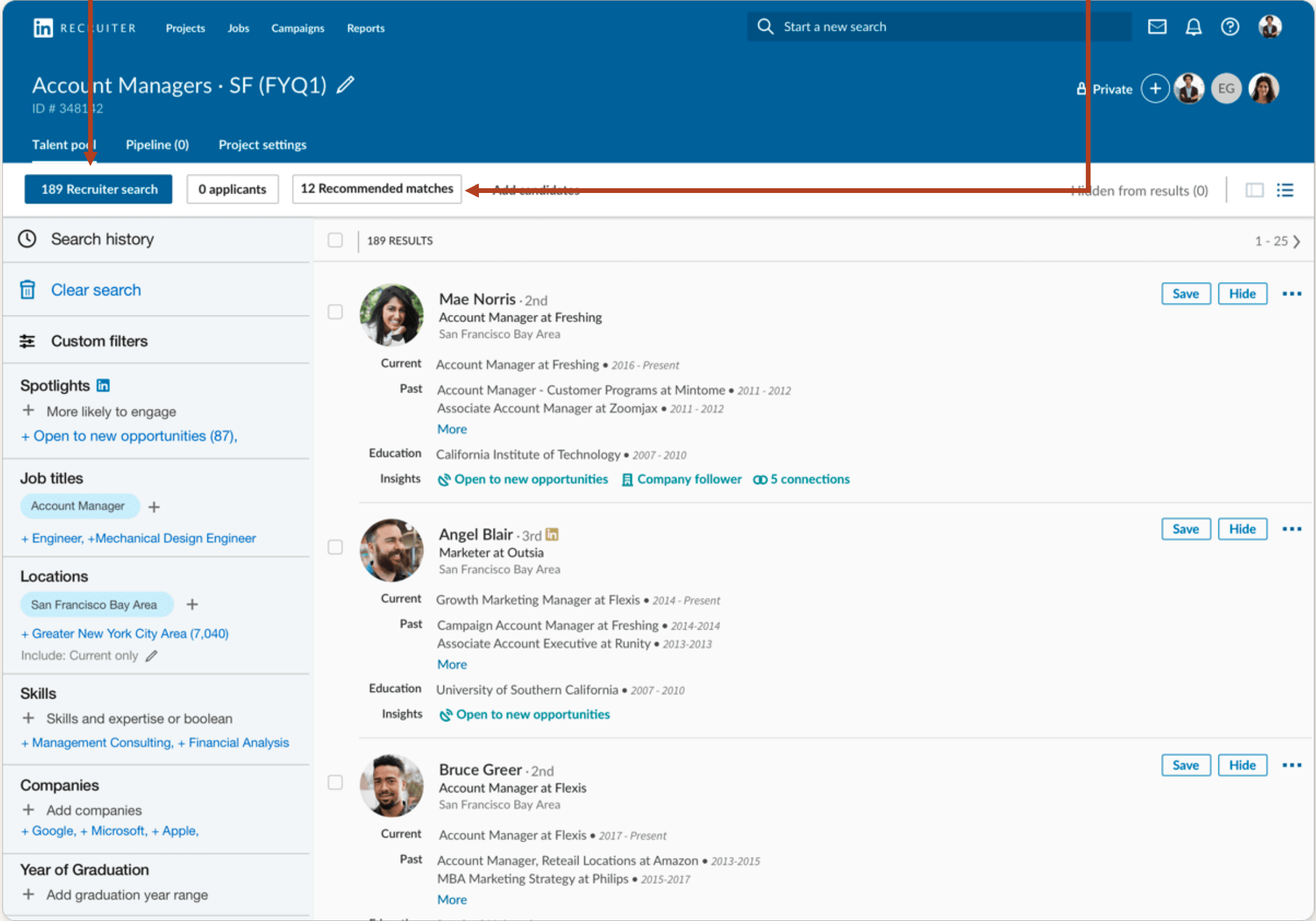
Job alerts



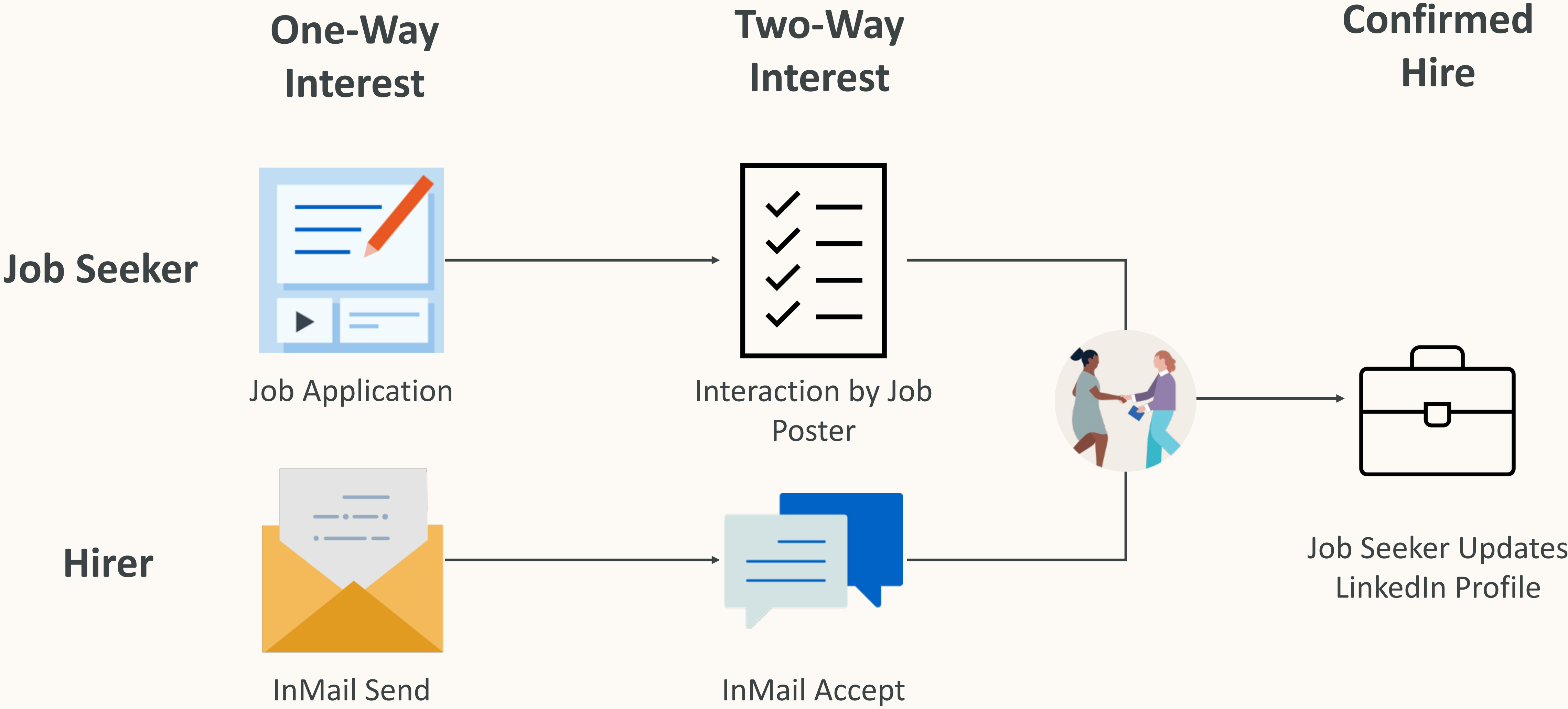
Hirers

Search for candidates

Candidate recommendations



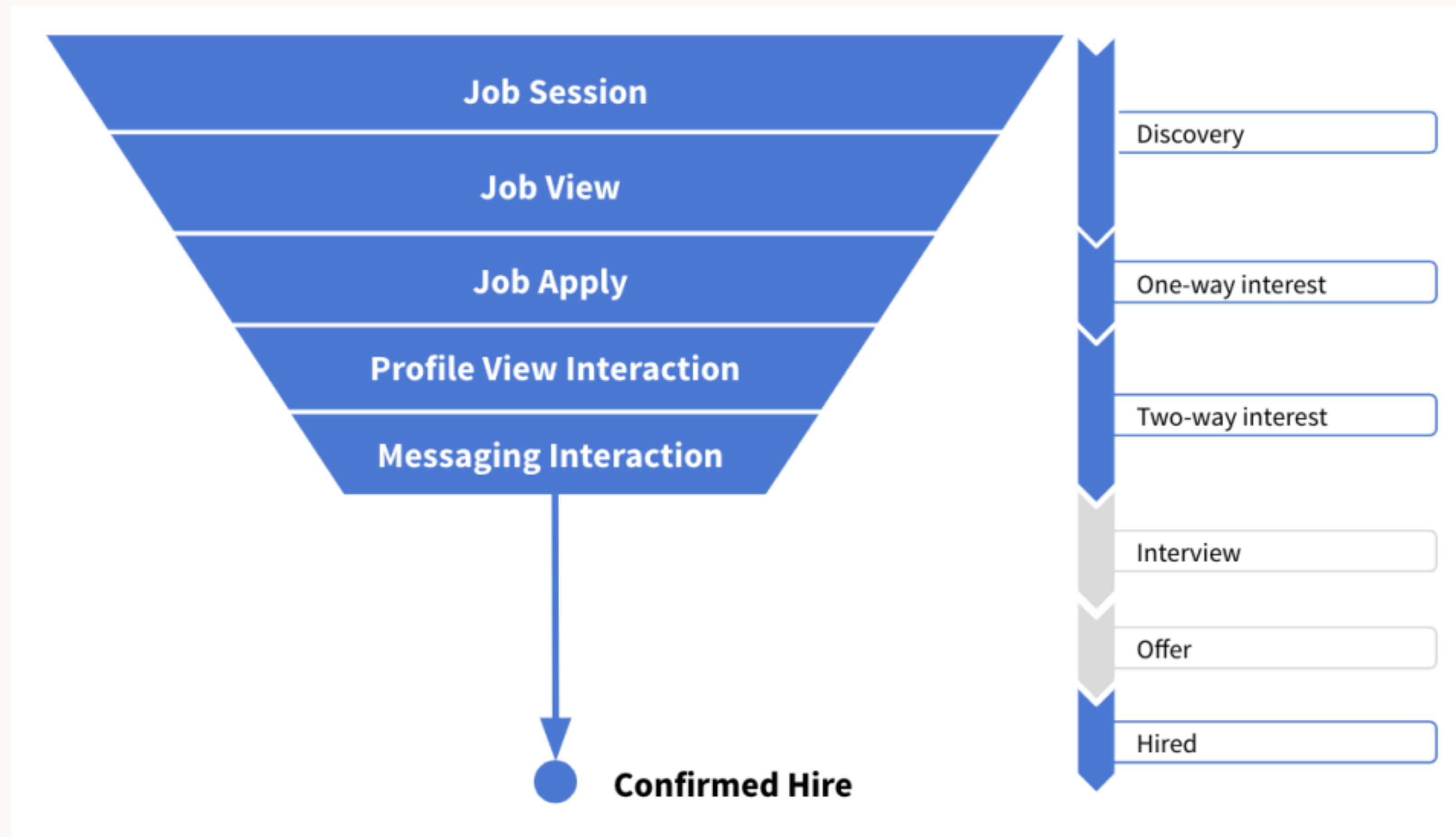
Path to a Confirmed Hire



Confirmed Hires as an optimization objective

Challenges (vs interest signals)

- Delayed by months
- Sparse
- Partially observable



Applications vs Hiring Outcomes

- Constraint: Each member can be hired into one job
- Result: Applications and hiring outcomes have a very different distribution



Source: <https://nypost.com/2017/07/26/royal-family-posts-job-ad-on-linkedin-gets-1000-applications/>

Solution: Use a surrogate metric for Confirmed Hires

Predicted Confirmed Hires (PCH)

Solution: Use a surrogate metric for Confirmed Hires

Predicted Confirmed Hires (PCH)

Finding a proper surrogate metric:

- High predictive power on the true north
- Focusing on metrics we can change and measure in the short term
- Customization for different treatment features
- Interpretability
- Management over head.

Also needs to satisfy *Statistical Validity Requirement*

Solution: Use a surrogate metric for Confirmed Hires

Predicted Confirmed Hires (PCH)

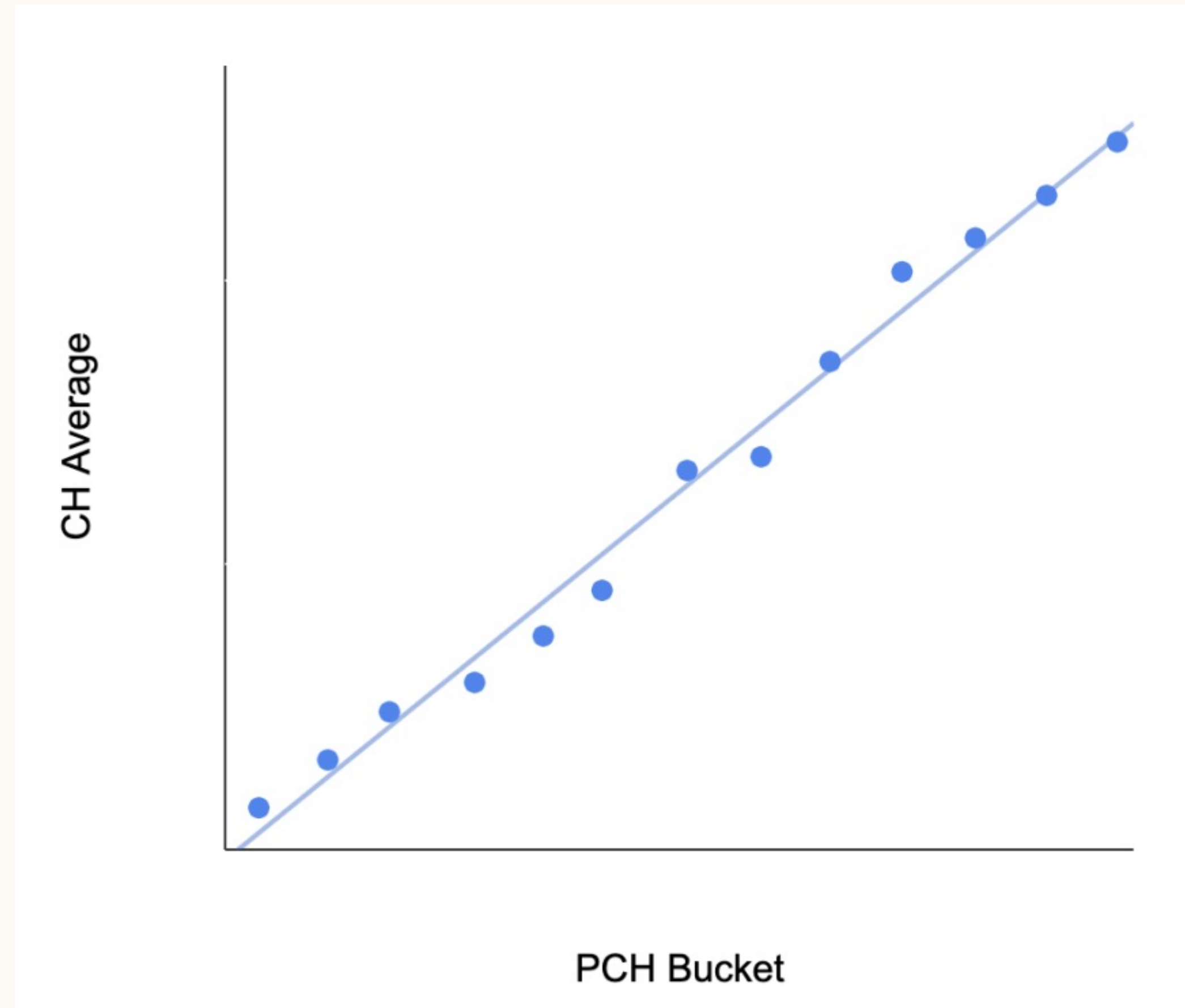
$$PCH = F(a_{jkqp}, b_{ji}, c_{ilqp}, d_{ij}, t),$$

where the notations have the following interpretations:

i	job seeker
j	job post
k	job application to a job post
l	job application from a job seeker
q	job segment
p	application quality signal
t	month when the application is submitted
a_{jkqp}	indicator variable representing whether the k th application to job posting j belongs to job segment q and has quality signal p
b_{ji}	number of applications received for job posting j after job seeker i applies
c_{ilqp}	indicator variable representing whether the l th application from job seeker i belongs to job segment q and has quality signal p
d_{ij}	number of applications already submitted by job seeker i after applying to job posting j




Solution: Use a surrogate metric for Confirmed Hires

Predicted Confirmed Hires (PCH)



Solution: Use a surrogate metric for Confirmed Hires

Predicted Confirmed Hires (PCH)

Metric Name 	% Change 	p-value 	Confidence Interval
Job Apply Predicted Confirmed Hire 6m	+0.84%	0.0034	[+0.28% , +1.40%]

Can't we rank jobs by PCH?

In Job Search, for example

Can't we rank jobs by PCH?

In Job Search, for example

Not directly, because the PCH model has access to information not available at ranking time (a.k.a., “privileged information”)

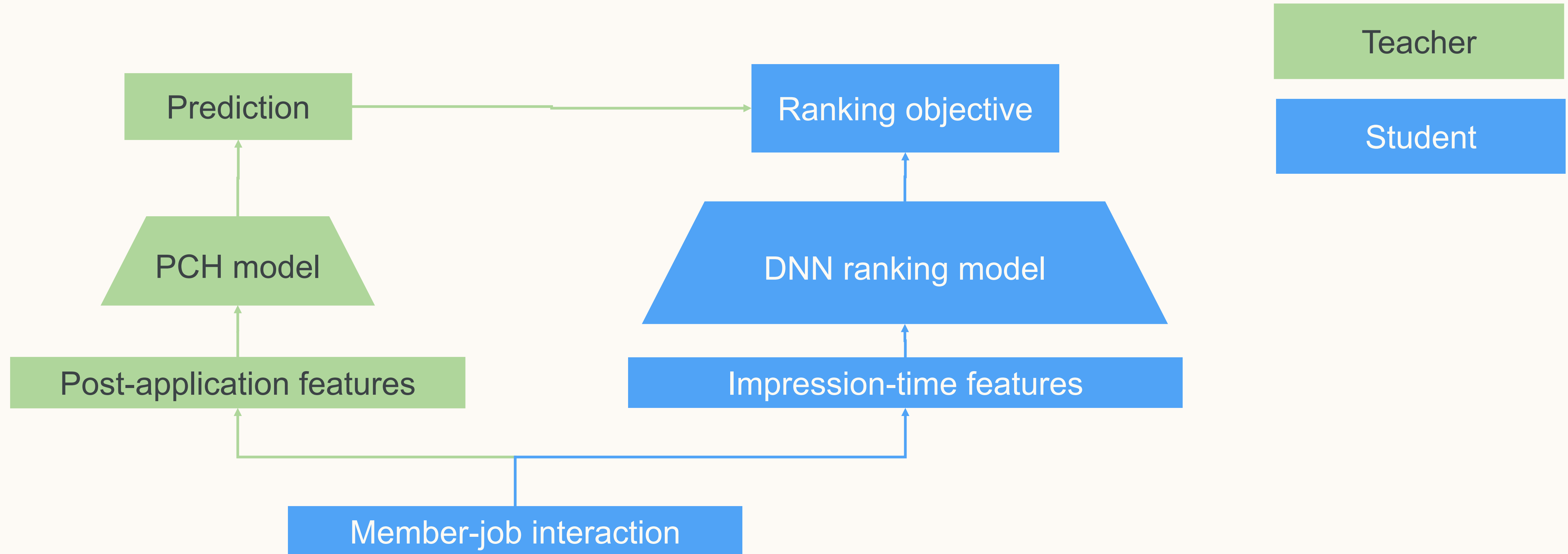
Optimizing rankings for hiring outcomes (I)

- Ranking models are DNNs built with a custom framework based on TensorFlow ranking
- Trained to optimize listwise Learning-to-Rank objectives where applicable
- Replaced: GLMM (GLMix) + GBDT (XGBoost)

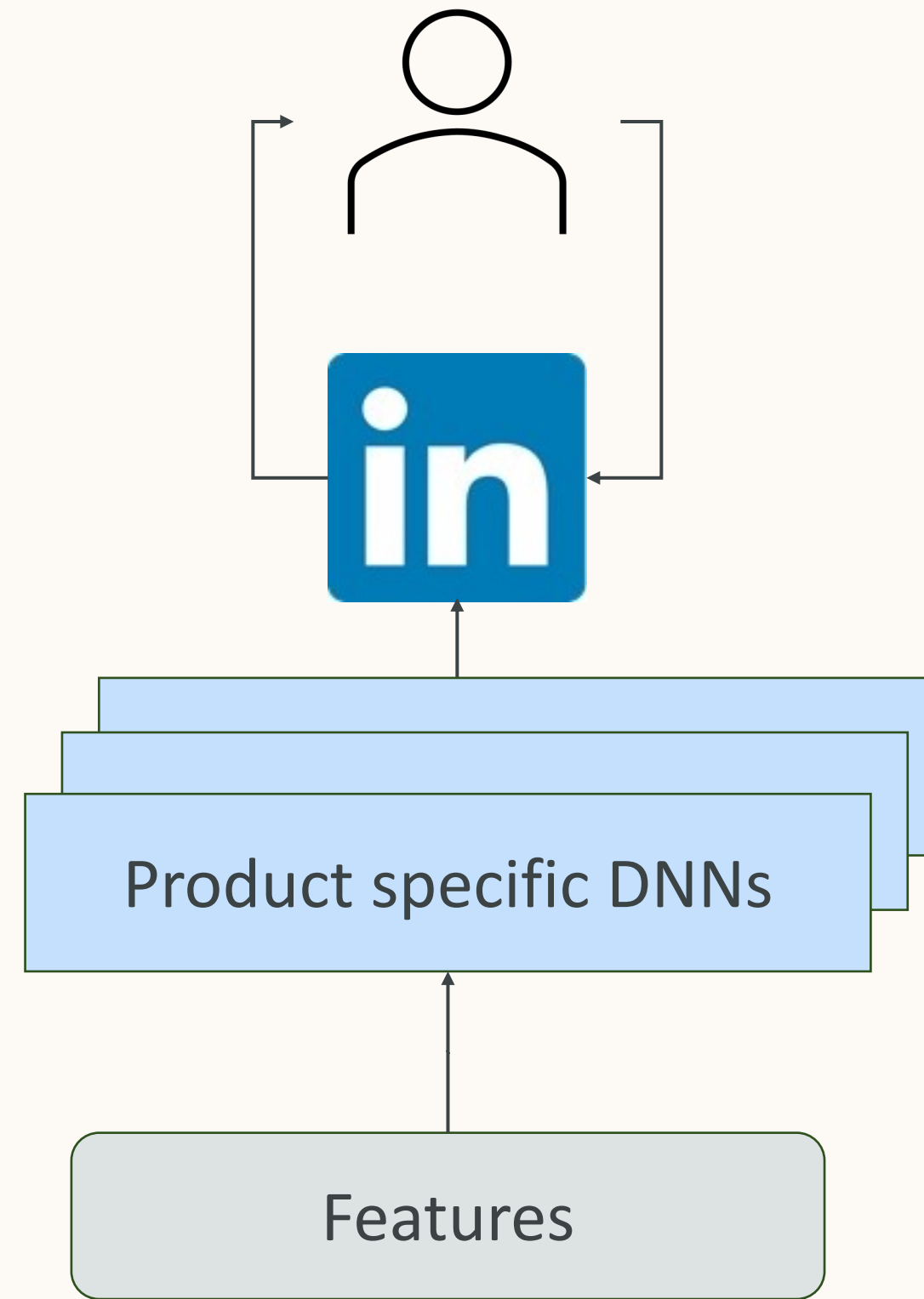


Optimizing rankings for hiring outcomes (II)

Using PCH as an optimization objective



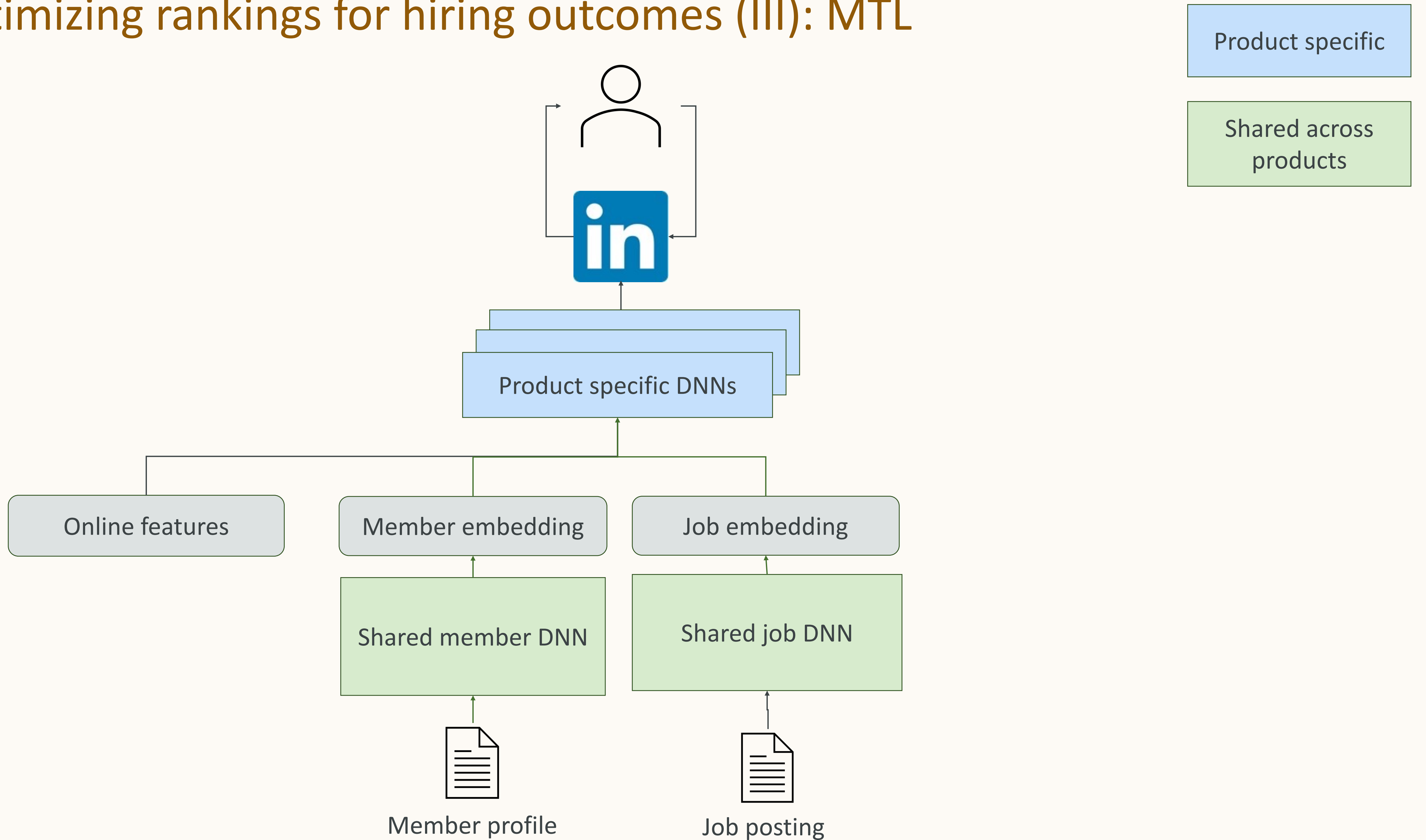
Optimizing rankings for hiring outcomes (III): MTL



Product specific

Shared across
products

Optimizing rankings for hiring outcomes (III): MTL





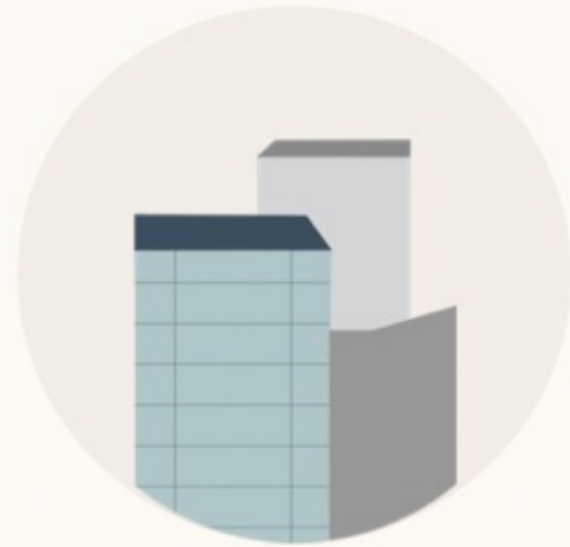
LinkedIn's Economic Graph

A digital representation of the global economy.



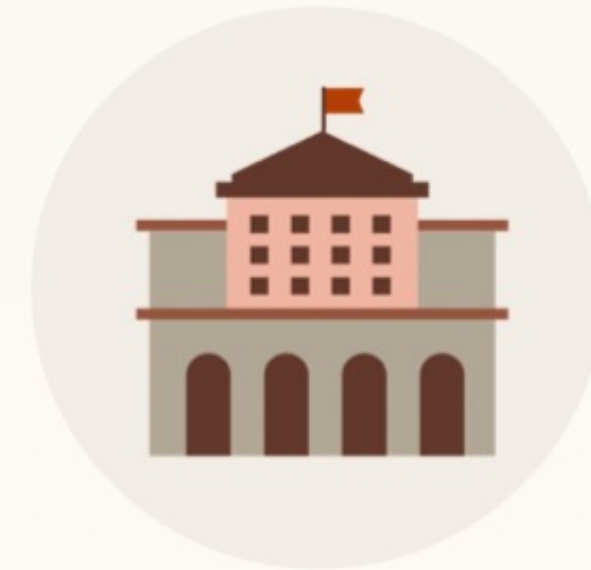
850M

Members



59M

Companies



128K

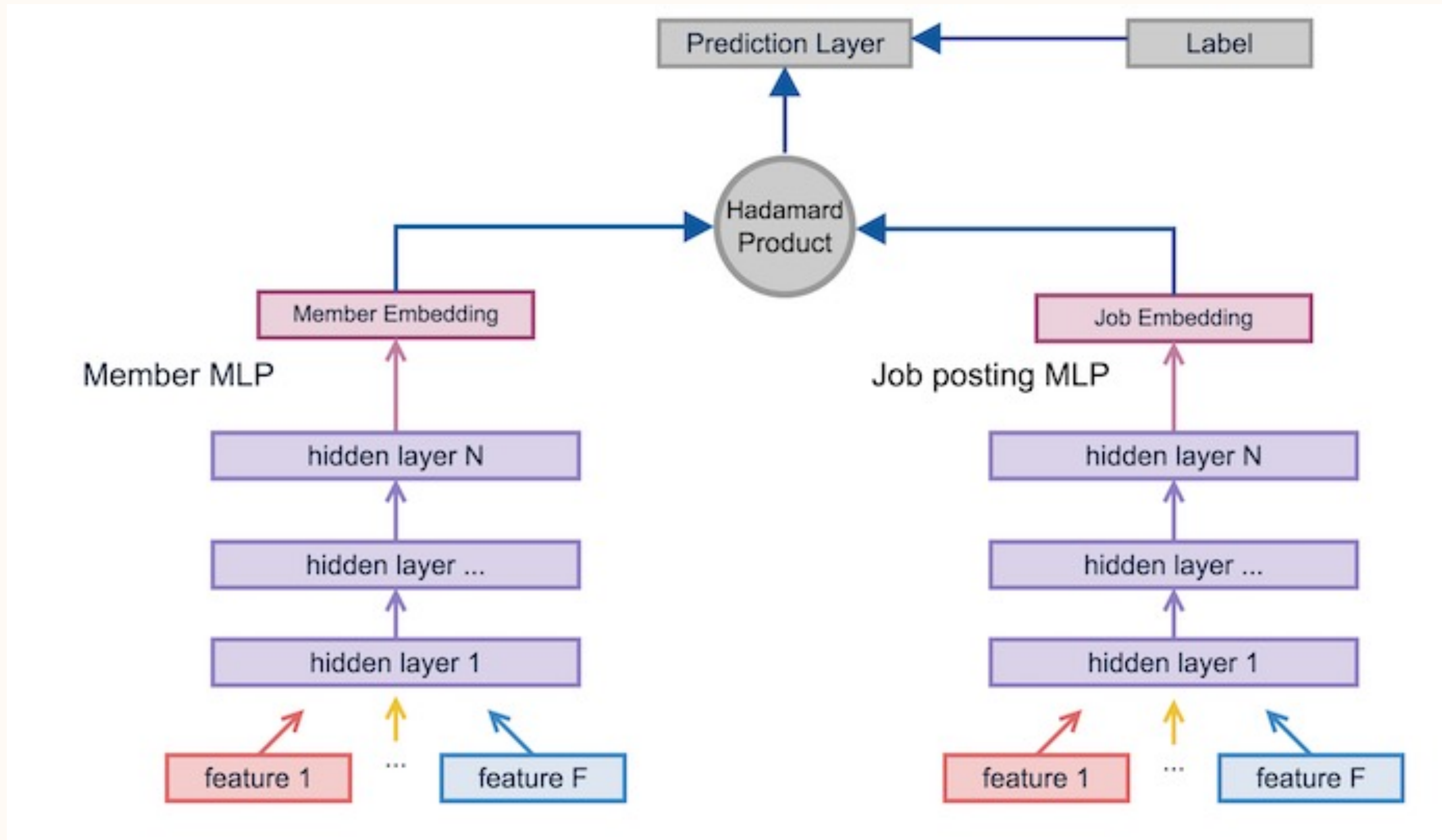
Schools



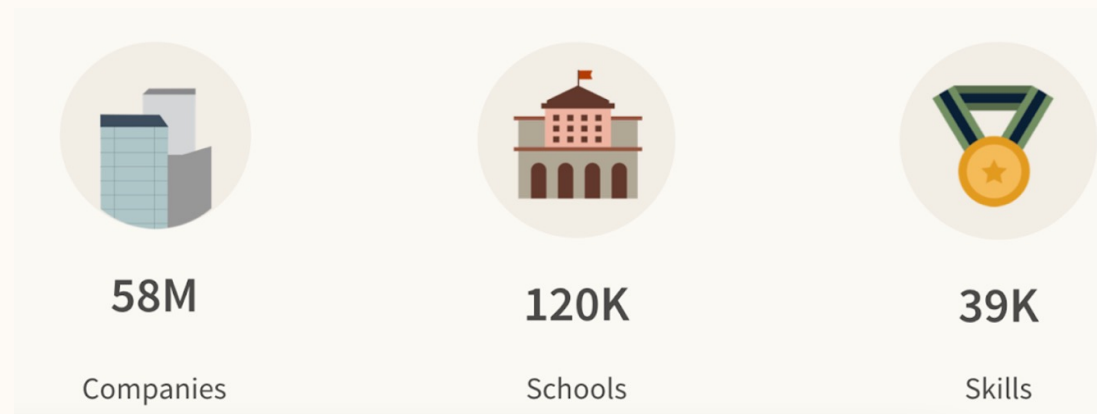
39K

Skills

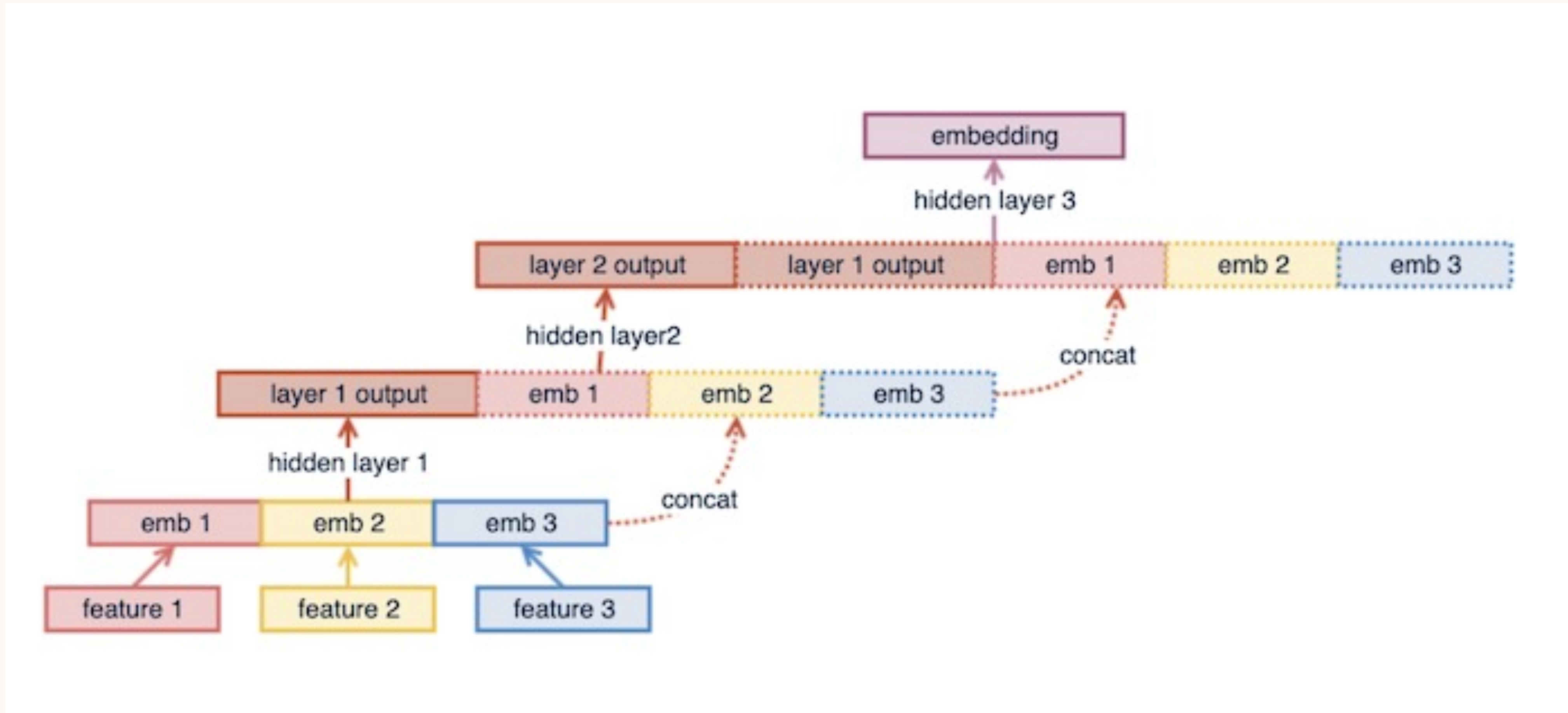
Pensieve 1



Economic Graph Entities



Pensieve 2



<https://engineering.linkedin.com/blog/2020/pensieve>

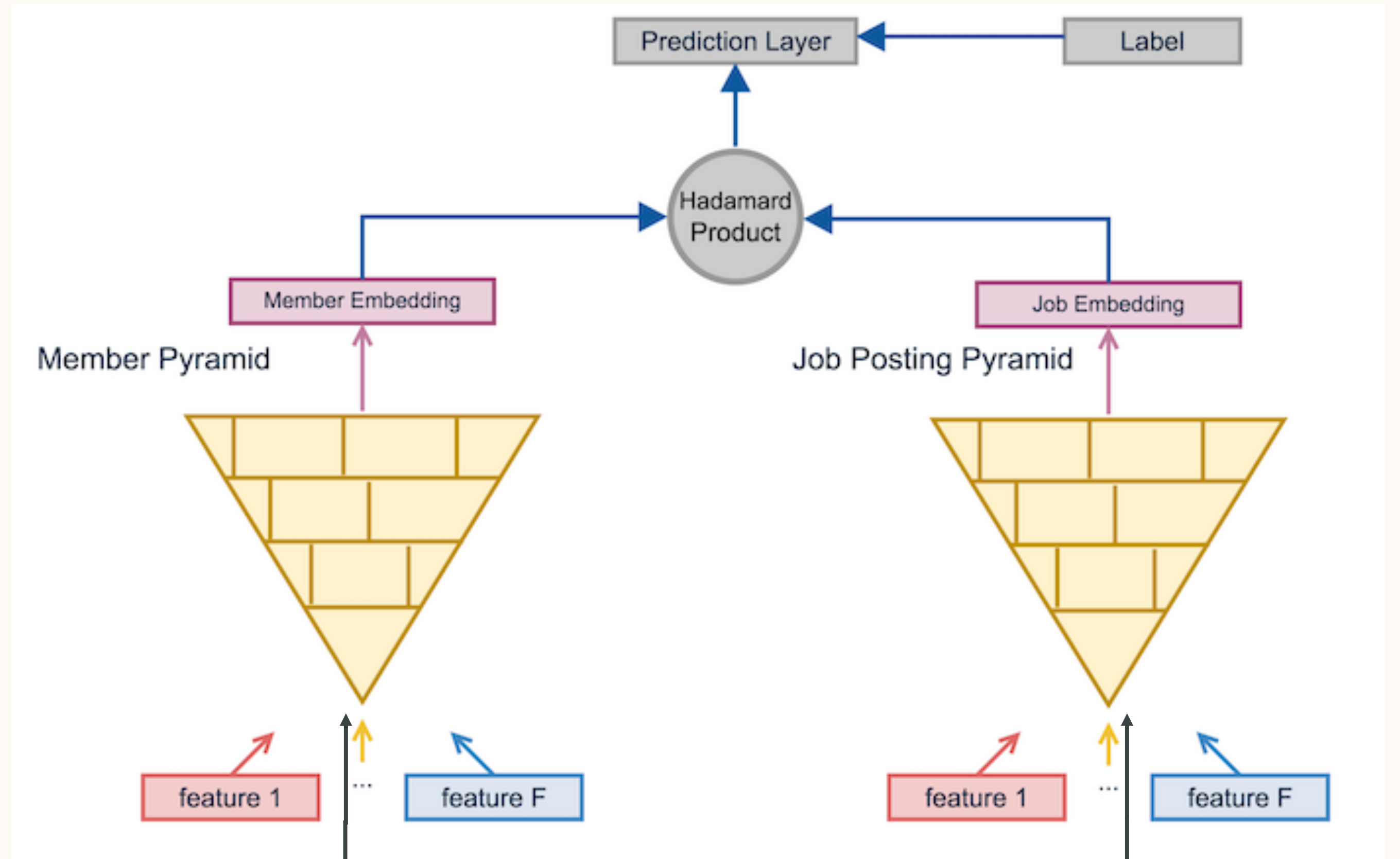
Pensieve 3

Language Model Pre-Training

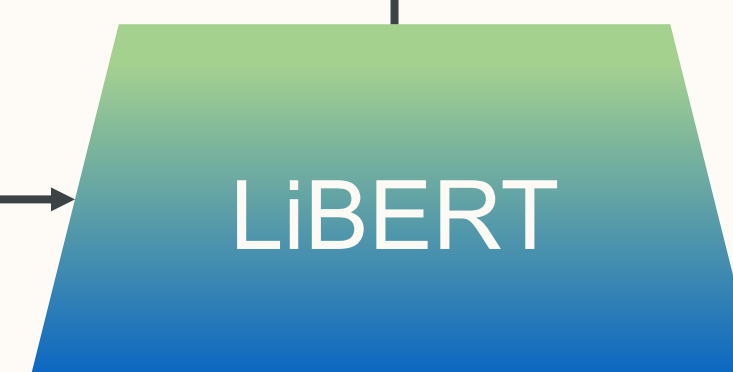


LinkedIn Text Context

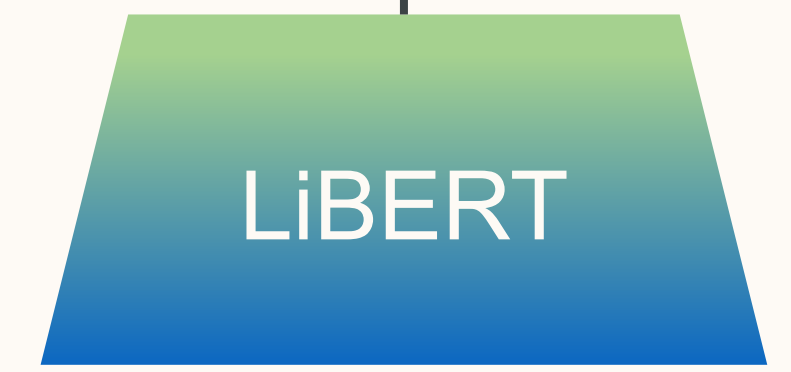
Guo et al. "DeText: A Deep Text Ranking Framework with BERT." CIKM 2020.



Fine-Tuning

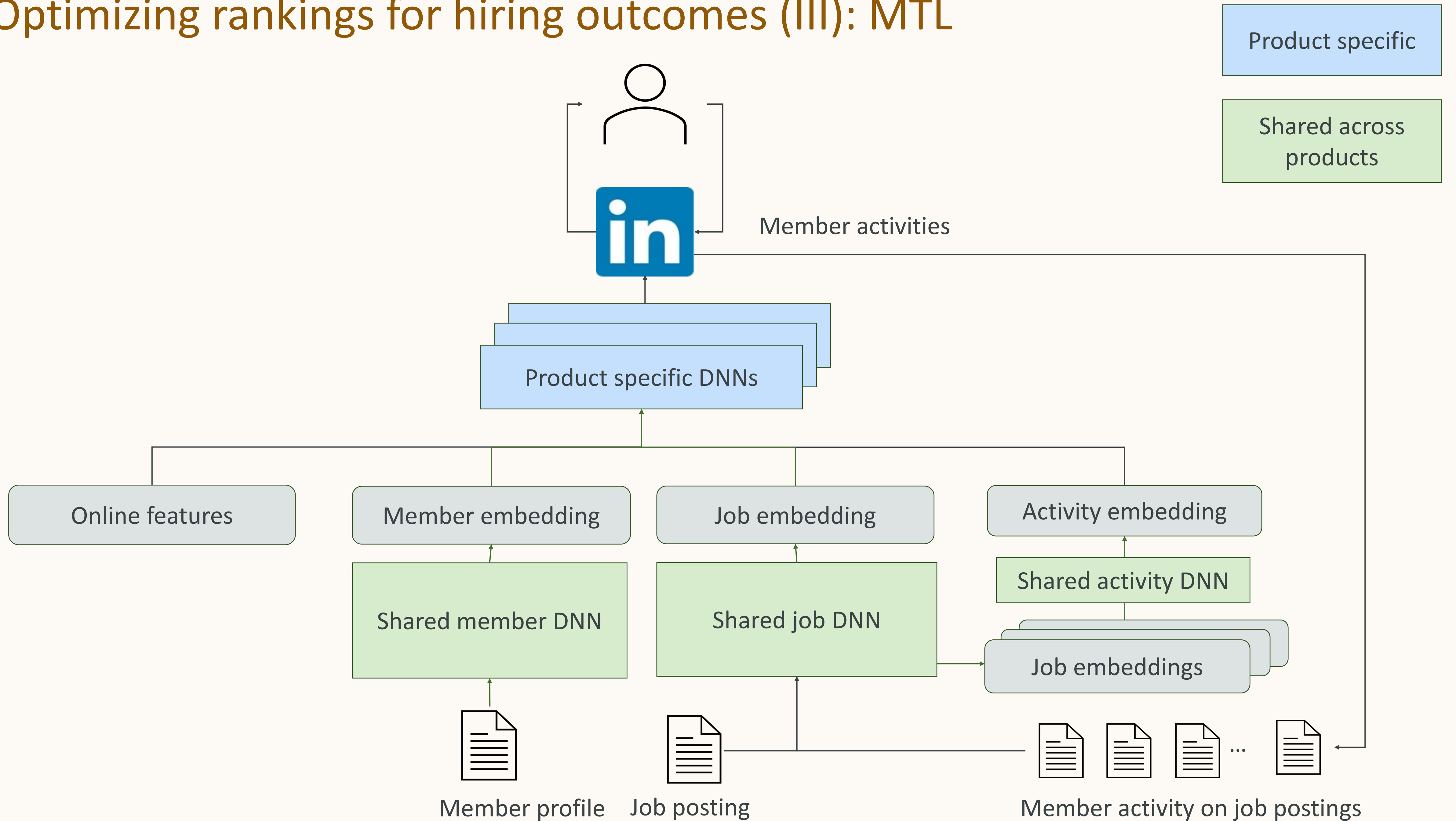


Member profile text

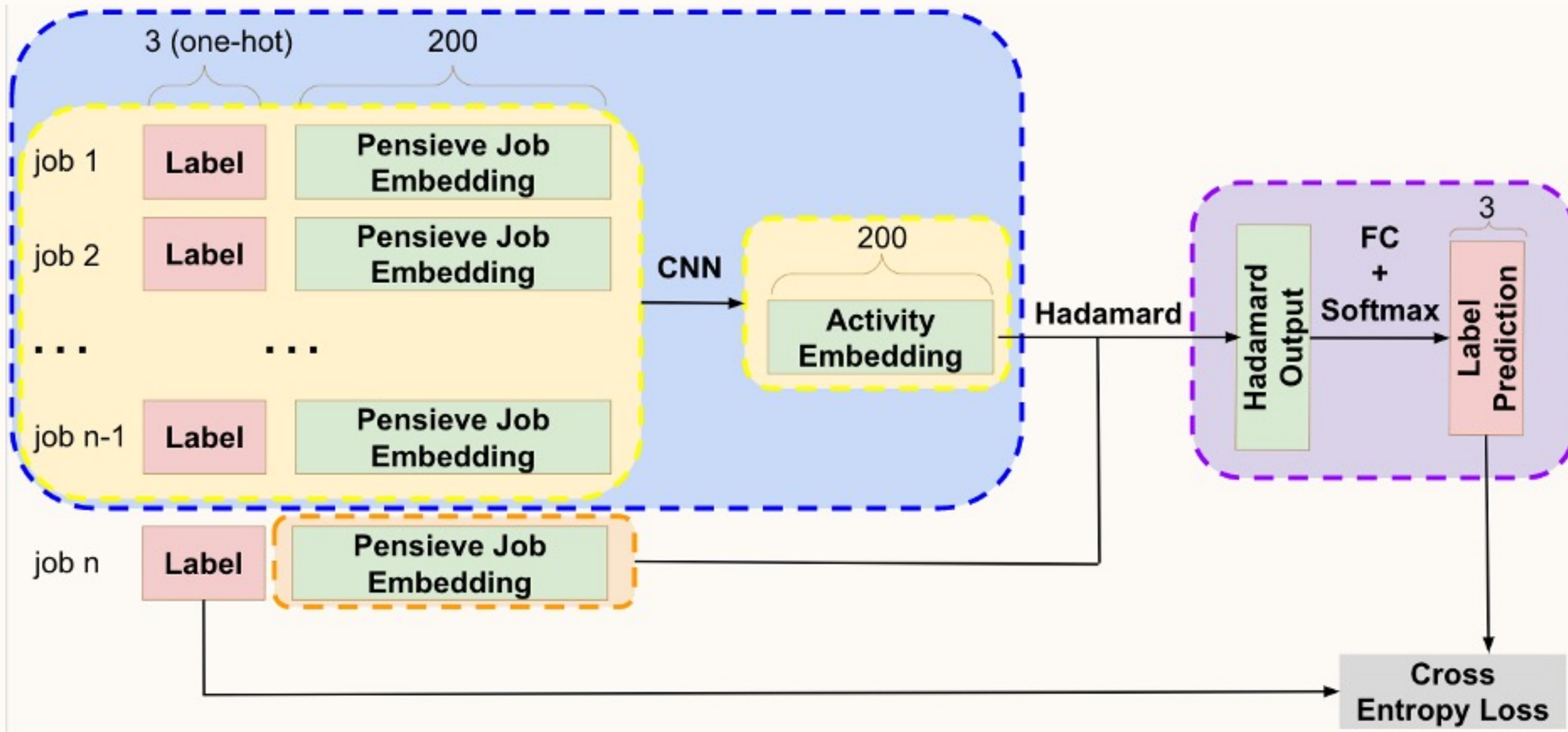


Job posting text

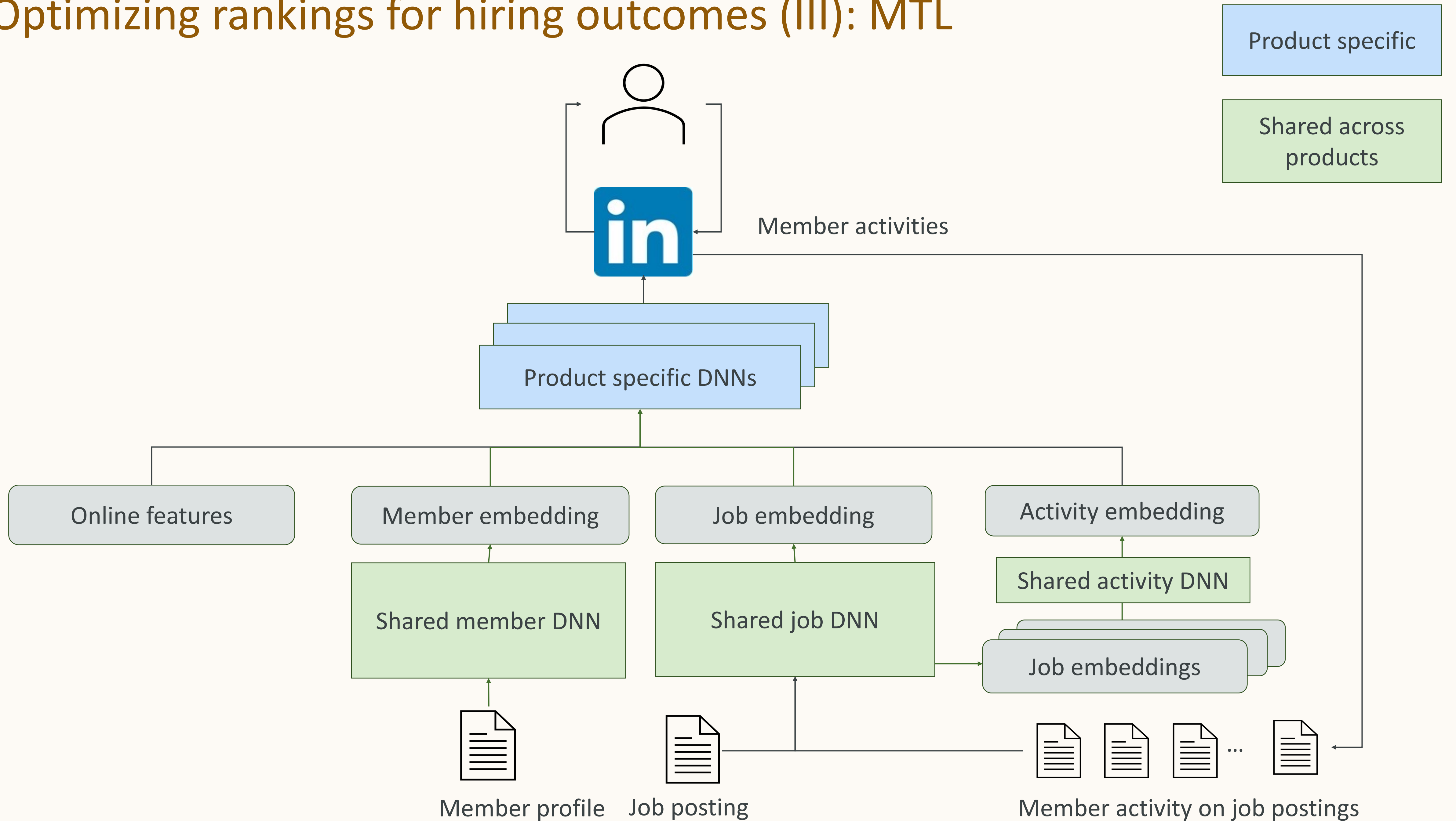
Optimizing rankings for hiring outcomes (III): MTL



Job-Seeker Activity Embeddings



Optimizing rankings for hiring outcomes (III): MTL



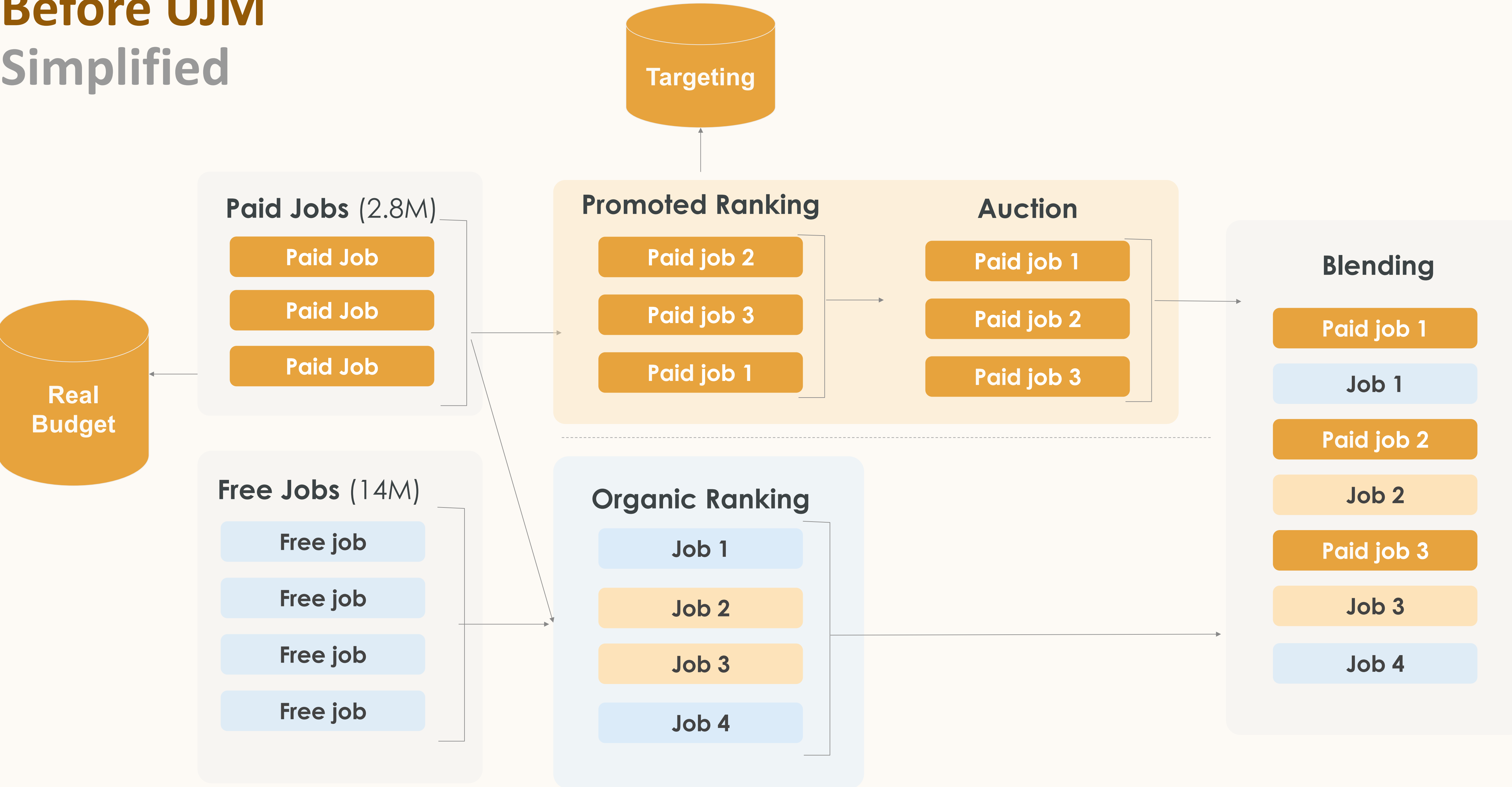


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Before UJM

Simplified



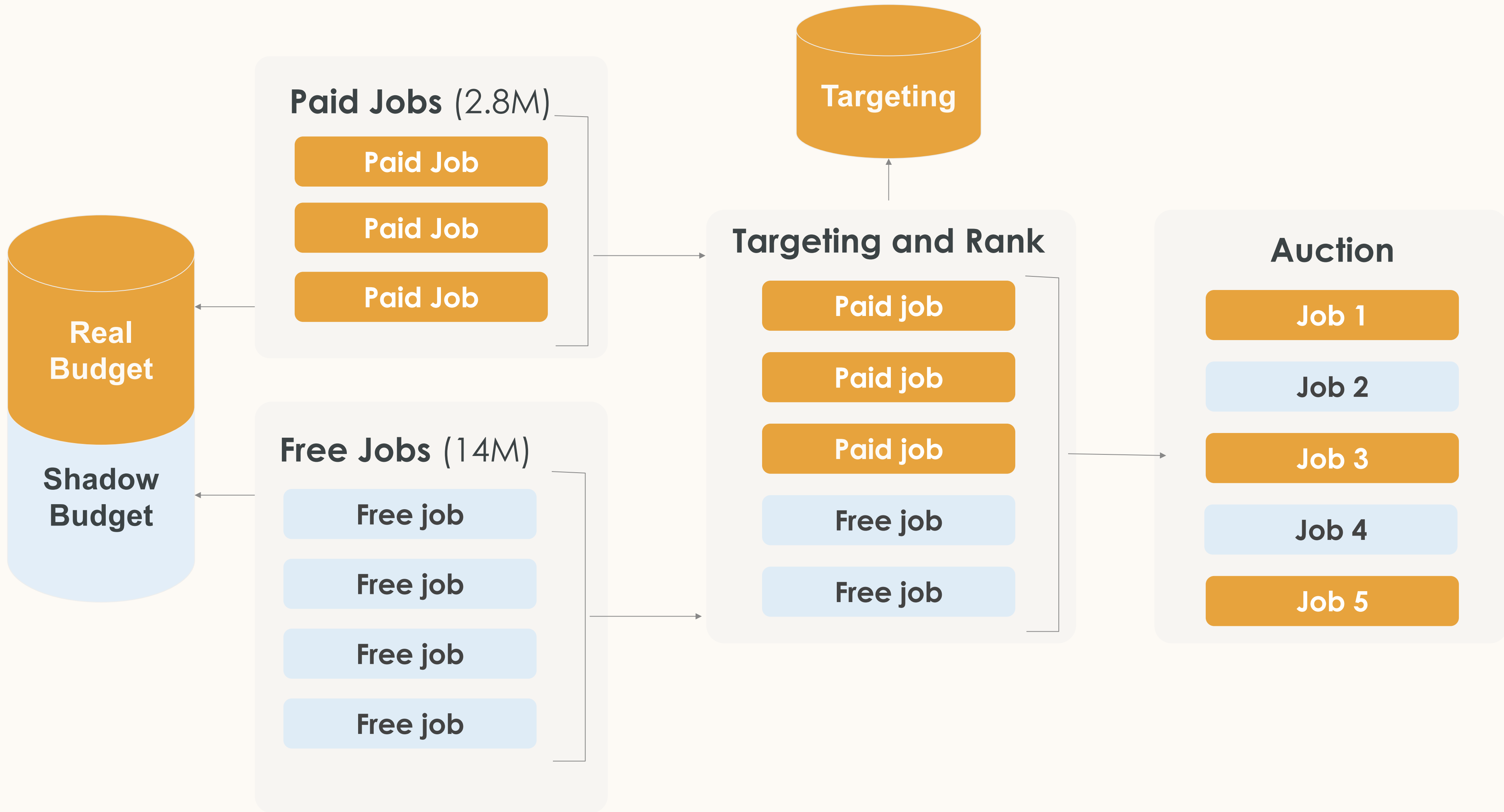
Unified Jobs Marketplace – Why?

- There is a need to provide **explicit** control over of Poster Value, Seeker Value, and LinkedIn Value (revenue) that the marketplace delivers.
- System should have explicit levers to control these three types of value, and these levers should work across the **entire product surfaces**, including search, recommendations, and notification channels.
- The new system should **simplify** the relevance stack and allow engineers to fast iterate solutions to better manage and deliver value in the jobs marketplace across all product surfaces.

Unified Jobs Marketplace

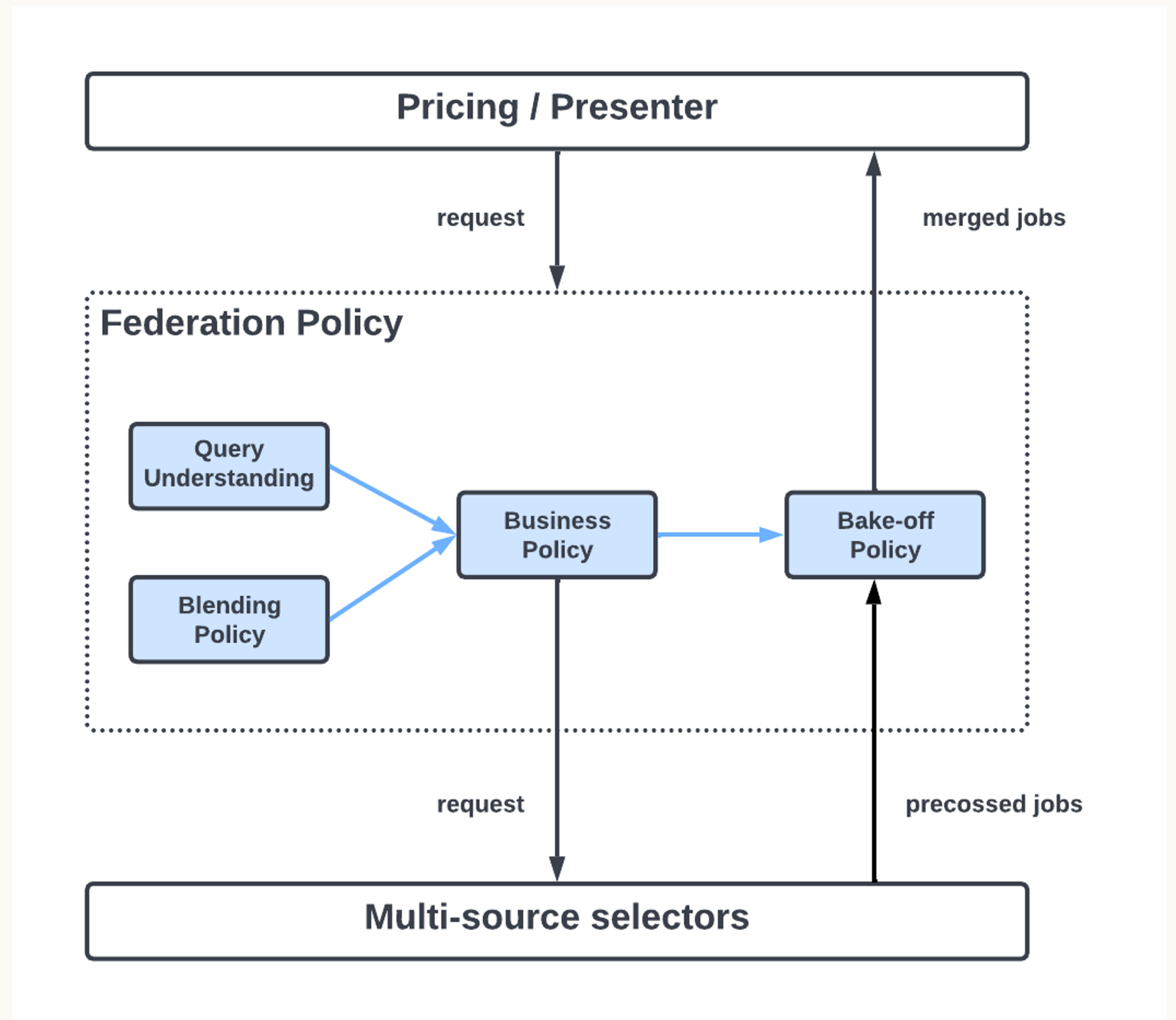
- UJM “Unified Jobs Marketplace” is a means to control value and to deliver value across both paid/free jobs in the marketplace via a unified currency.
- All jobs - free and paid - will participate in the same relevance pipeline (candidate sourcing & federation, auction, and presentation). Free jobs will participate in the auction alongside paid jobs with a “shadow budget” and “spend” to receive engagement. We will stop actively distributing jobs once they run out of “shadow budget”.

Controlling Free and Paid Value through UJM



UJM Component - Unified Selector Platform

- **Federation Policy**
Provide the hybrid levers (automatic or manual) by using the 3B Policy (Blending, Business, Bake-off policy) to make trade-offs among different values based on context differences.
- **Unified L1 Scoring Model**
Reduce the number of L1 ranking modeling pipelines from 4 to 1.



UJM Component - Unified Selector Platform

When launching USP, the unified models show:

- **+1.5%** in Revenue
- **+1.3%** Matching

vs. the legacy models across Recommendation and Job Search Organic and Promoted channels.

UJM Component - Shadow Budget

- Shadow budget is a tool to allocate seeker traffic for job postings according to marketplace objectives such that overall engagement is maximized. This tool works in conjunction with the job poster's committed "Real Budget" to form a "Total Budget".
- Job Marketplace then utilizes the "Total Budget" to determine the amount of exposure (impression) and engagement (views, applies) that a job posting would receive throughout its lifecycle. Shadow budget is optimized to maximize engagement such that business constraints are met.

Market-level Assignments

$$pvp_i = \frac{Engagement_{rb,i}}{Engagement_{sb,i} + Engagement_{rb,i}} = \frac{RB_i}{SB_i + RB_i} \quad (2)$$

$$SB_i = RB_i \times \left(\frac{1}{pvp_i} - 1 \right) \quad (3)$$

Segment-level Allocation

$$sb_{p,i} = \frac{1}{numJob_{p,i}} \times SB_i \times ctr_{p,i}^\alpha \times numJob_{p,i} \times \frac{1.0}{\sum_{i=1}^k ctr_{i,s}^\alpha * numJob_{i,s}} \quad (4)$$

Main Levers for Controlling the Marketplace

- **Shadow Budget**
Lever for almost all major metrics (engagement, QA, relevance, free value Vs. paid value, FJ Vs. OJ)
- **Blending Policy**
Balancing the liquidity between paid job and free jobs.

UJM General Access Launch

Launch is a win-win-win for Member, Customer, and LinkedIn value with:

- **+1.8%** Revenue
- **+0.2%** Job Sessions,
- **+4.0%** Paid Job Qualified Applications (paid customer jobs), and **+0.5%** total Qualified Applications

along with wins in engineering infrastructure scaling to auction **8x** more jobs and experiment velocity.



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UJM System

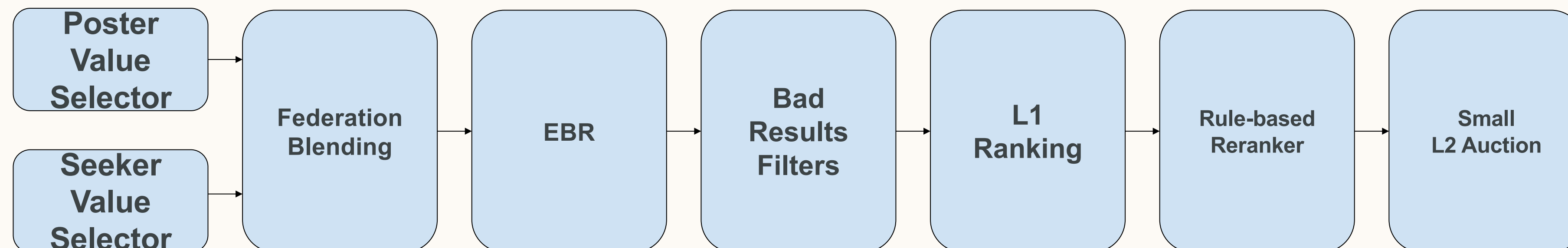


Challenges After UJM

- **Low Productivity:** We have several stages of retrieval, early ranking, and early filtering that are manually updated on demand. AI engineers need to do more work to develop a new model for one of the several stages, as updating one stage may cause break another stage.
 - **Marketplace Value Generation:** The design of these stages does not ensure that they are aligned with the true real-time auction, so real-time auction value (Clicks, Applies, Bad Matches) is not as good as it could be.
-
- **Slow Bidding:** Jobs server is incapable of bidding on RTB requests that have an SLA under 300ms.
 - **Inelastic Auction:** Incapable of generating more marketplace value if given more time, more computing resources.

UJM: Small Auctions

- Current jobs marketplace is designed using “small auction” semantics
- Several stages of retrieval and intermediate stages of ranking and filtering models gate the entry to the auction
- Business logic & critical responsibilities are coupled across the stages
- Keeping the stages aligned is a fragile, manual process that impedes developer productivity
- Lack of alignment between stages limits auction revenue generation
- Lost revenue is not measured in real-time!



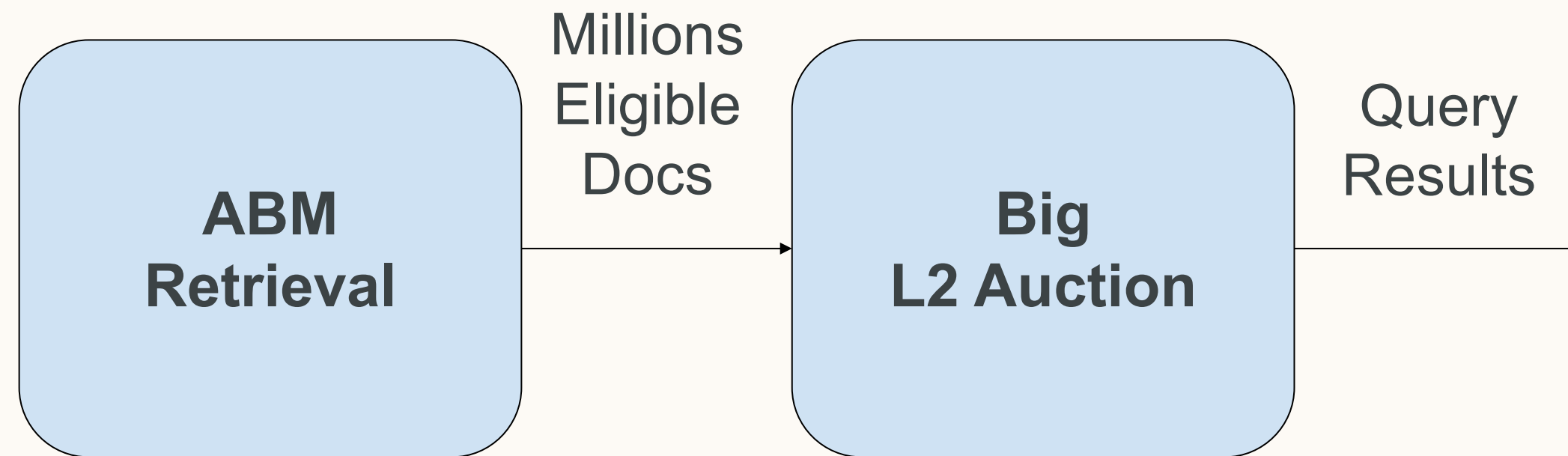
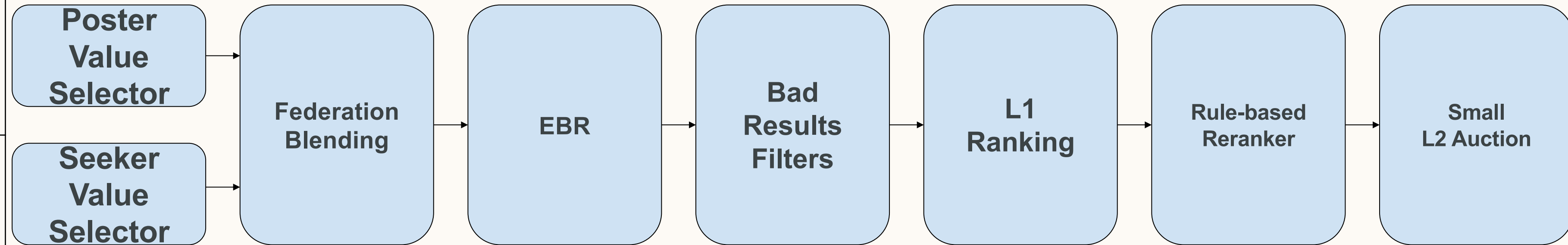
Introducing Big Auctions

“Big Auctions” is a means to streamline jobs marketplace value delivery across the multiple stages of the jobs marketplace serving and AI matching engine:

- Jobs marketplace behaves as though it is one big auction. Under the hood: serving will run two auctions: a *fast* big auction, and *slow* final auction.
- Retrieval will be implemented as a fast big auction. Fast big auction is automatically aligned with the results of running the slow final auction on everything.
- The final auction runs on the winners of the first auction to correct any mistakes. Auction is designed so that marketplace value monotonically increases as the depth of the auction increases

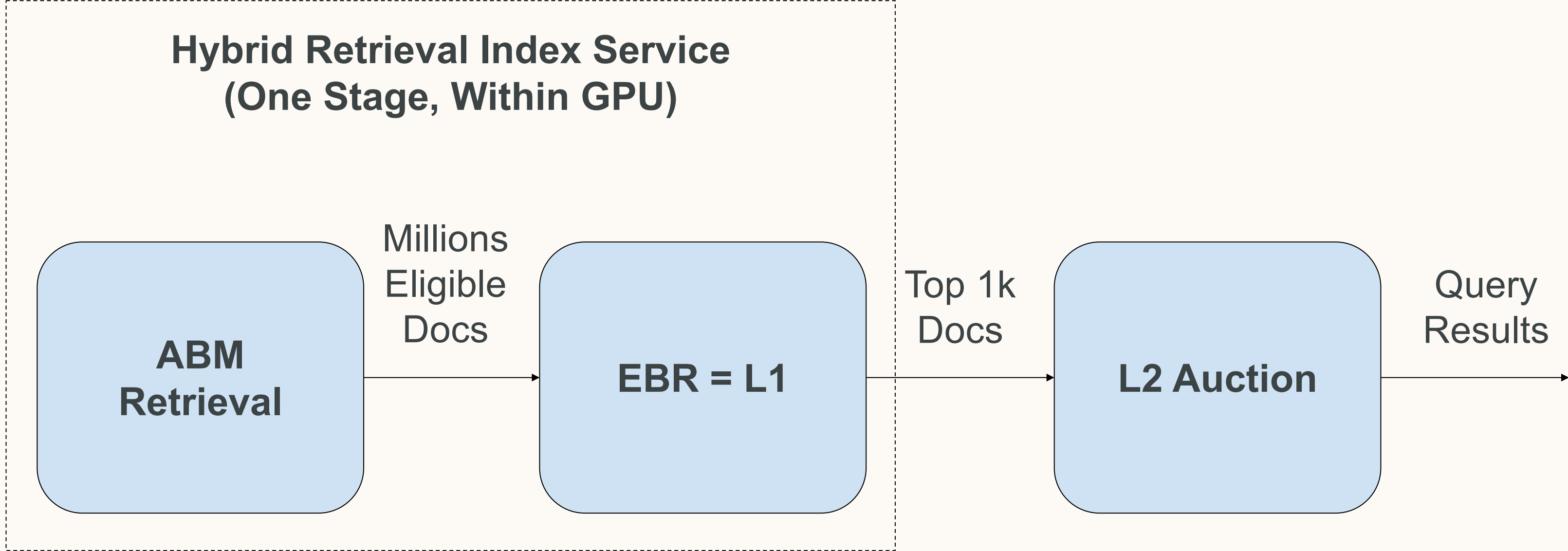
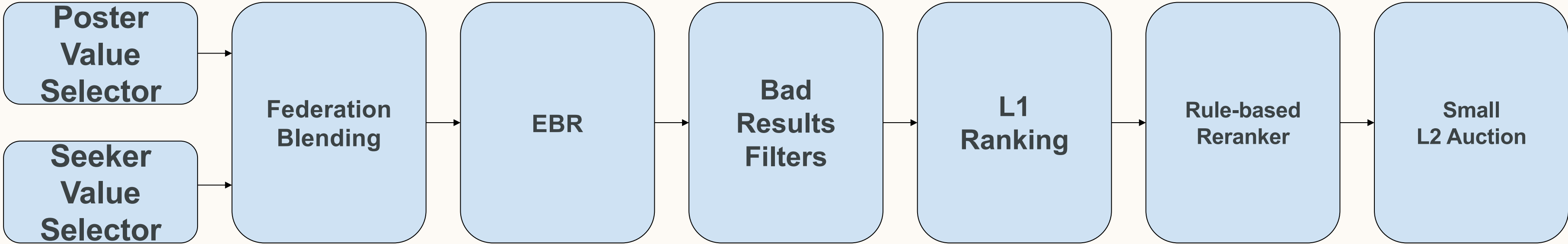
Small Auction vs Big Auction: Ideal & Unscalable Solution

Stages Responsible	Small Auction	Big Auction
Job Valuation Assignment (revenue, facepalms)	<ul style="list-style-type: none"> - Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2 	- L2
Scalability	<ul style="list-style-type: none"> - Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2 	???
Multi-stage Alignment	<ul style="list-style-type: none"> - Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2 	???
Quick Fixes: Facepalms, Boosts	<ul style="list-style-type: none"> - Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2 	- L2



Big Auction: Scalable, but no guaranteed alignment

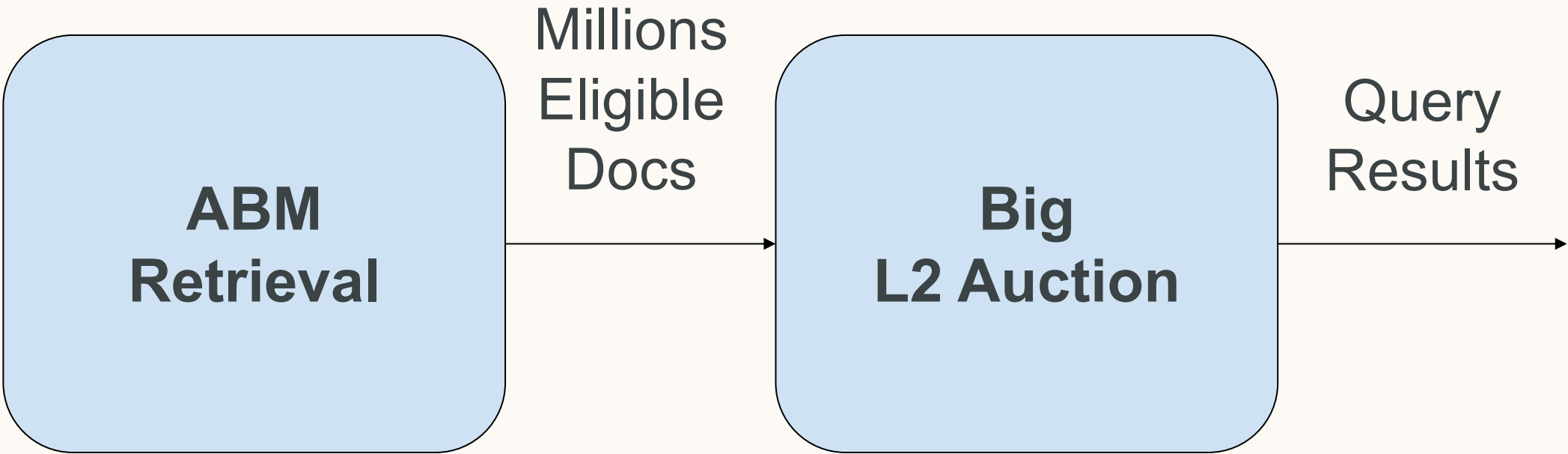
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Quick Fixes: Facepalms, Boosts	<ul style="list-style-type: none"> - Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2 	- L2



Big Auction: Counterfactual Reasoning

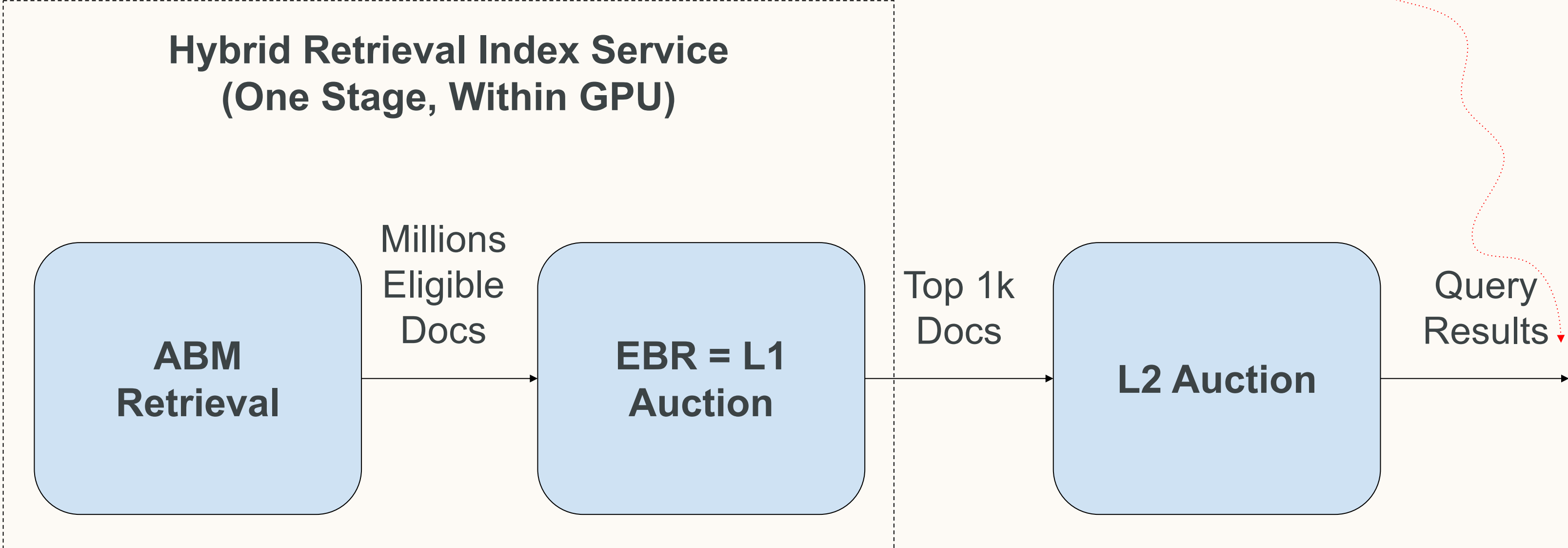
Counterfactual Serving Path

(1% of traffic, high latency, doesn't send results to user)



Actual Serving Path

(100% of traffic, low latency, sends results to user)



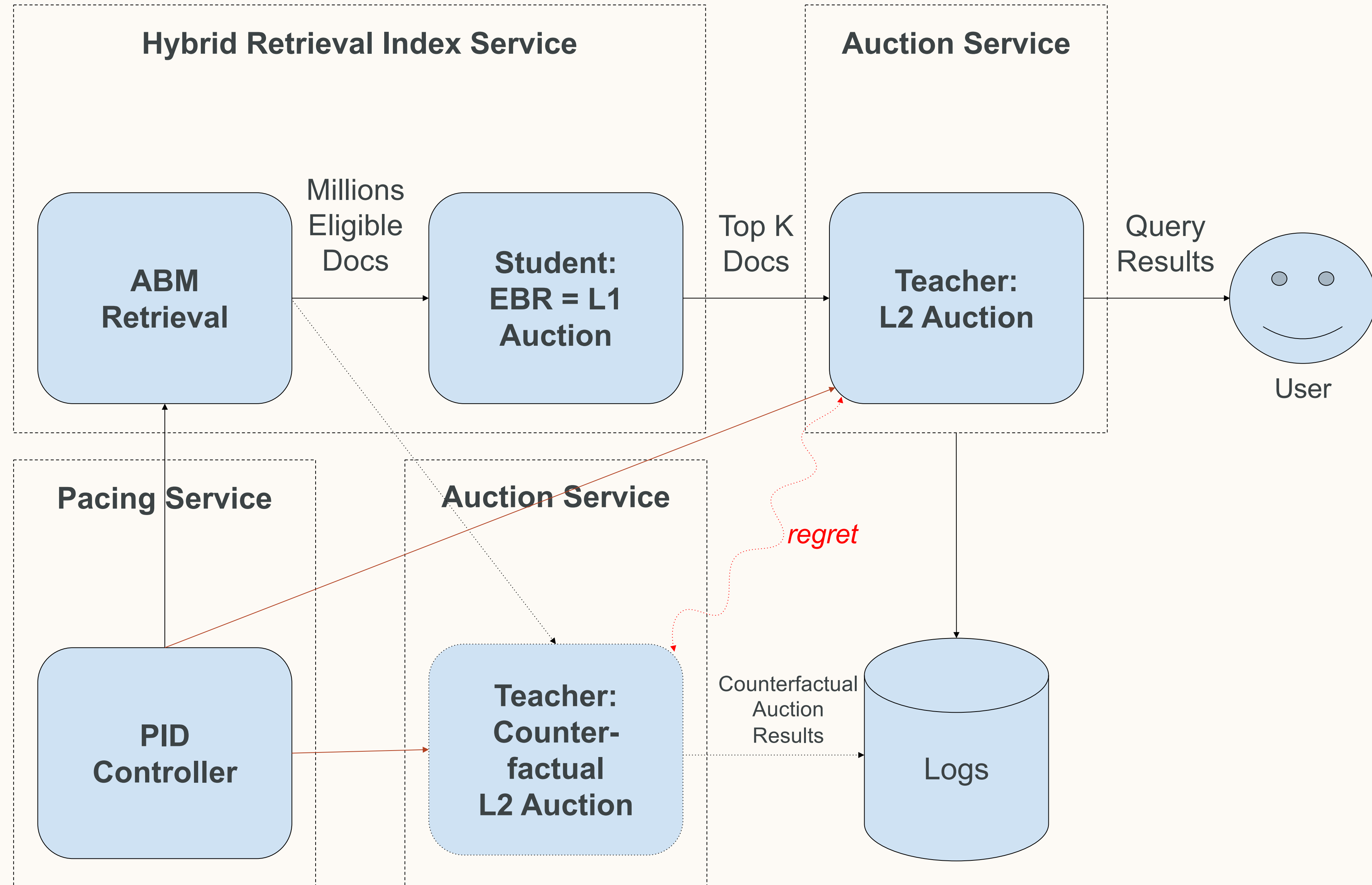
Measure Alignment

- **Auction Counterfactual Regret**
Measure of budget-unaware revenue lost due to imperfect alignment between retrieval & multi-stage ranking.
- **Track in real-time** using counterfactual logging
- “Big Auction” system architecture is inspired by RL’s fictitious self-play and counterfactual regret minimization.

$$Regret = E_q \left[1 - \frac{\sum_{d \in Sk(q)} T(q, d)}{\sum_{d \in Tk(q)} T(q, d)} \right]$$

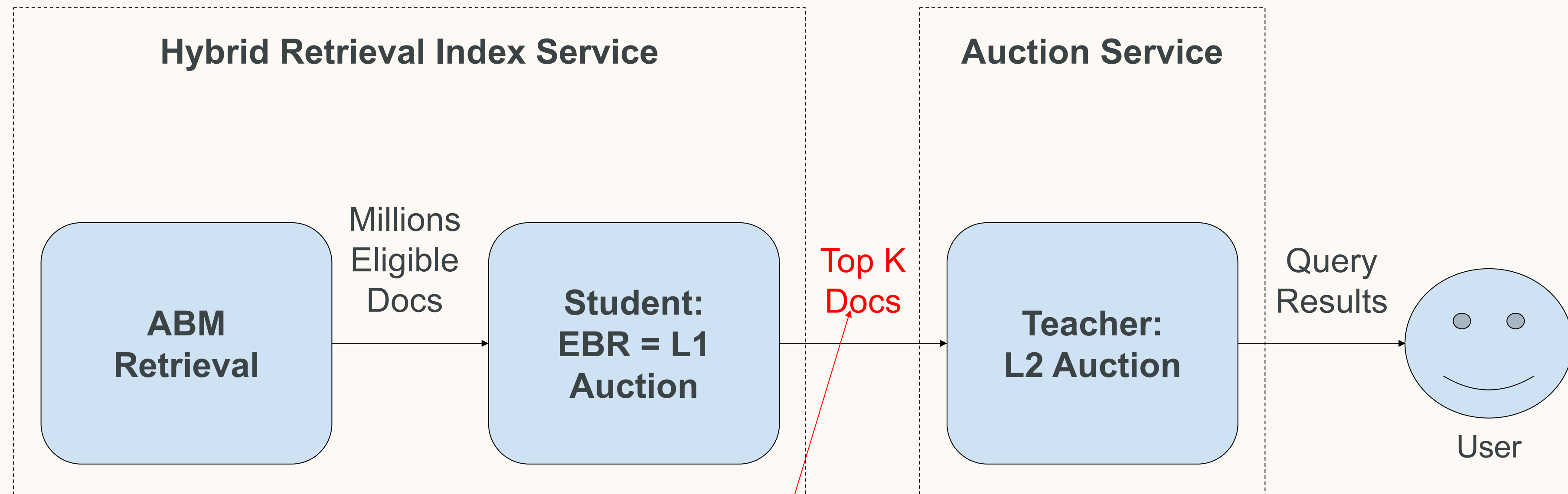
Big Auction: Scalability & Automatic Alignment

- Auction Counterfactual Regret Minimization
- L1 Auction is a student of the L2 Auction (the teacher)
- Real-time auction regret tracks how approximate the student is
- The teacher debiases the student
- Hourly online learning improves debiasing
- Filtered EBR within GPU ensures scalability
- Control systems elastically allocate serving resources in real-time to minimize regret



Big Auction: Elastic L2 Auction Depth

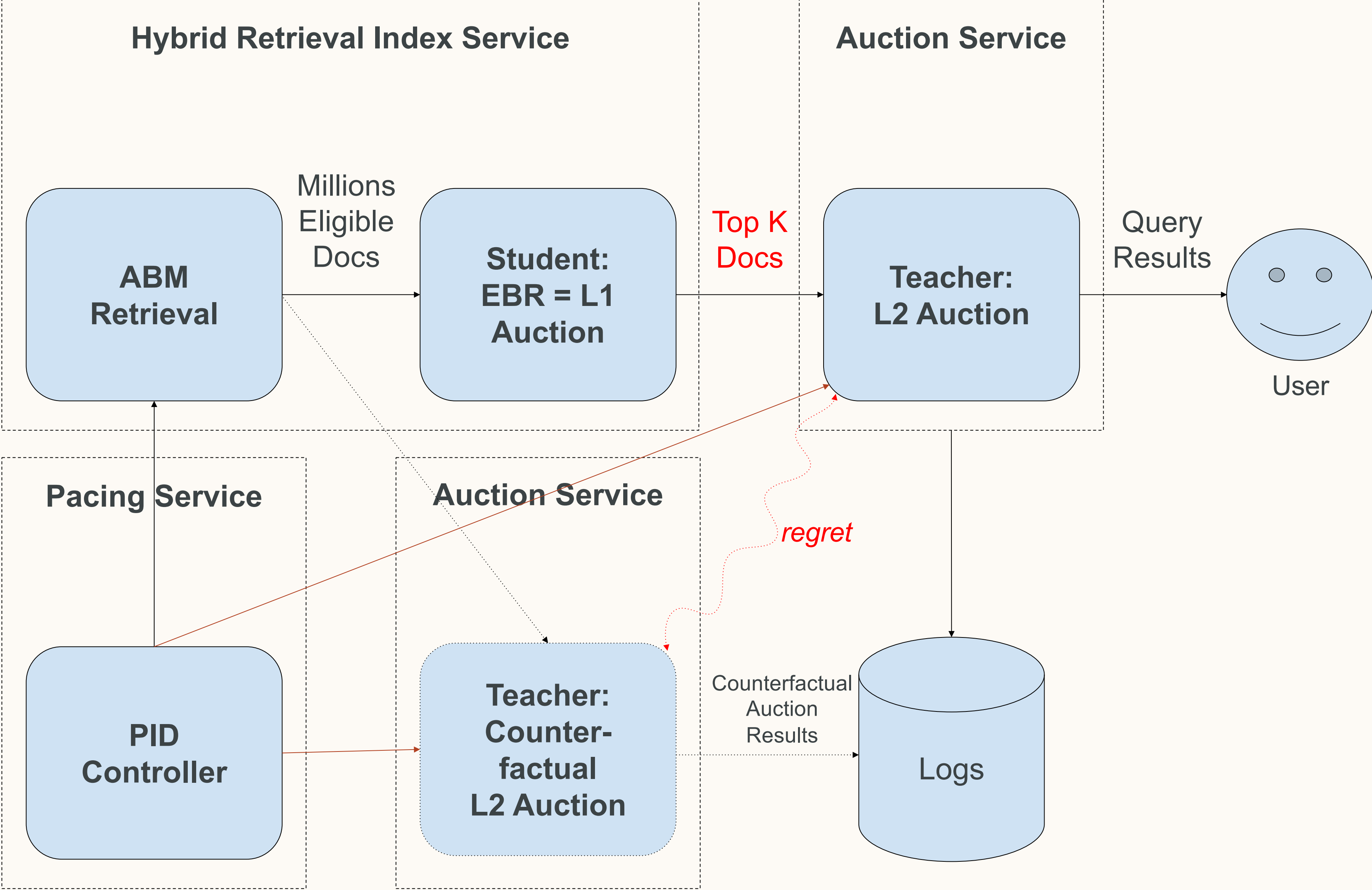
- EBR Auction selects the top K
- K is dynamically calculated for each request
- $K = (TMAX - preL2MS) * avgL2DocsPerMS$
- TMAX = request-level parameter setting max allowed latency in milliseconds
- preL2MS = latency spent by everything before L2 auction
- avgL2DocsPerMS = real-time moving average of the number of documents that L2 auction can process per milliseconds



Regret decreases as auction depth increases!

Big Auction: Scalability & Alignment

Stages Responsible	Small Auction	Big Auction
Job Valuation Assignment (revenue, facepalms)	- Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2	- L2
Scalability	- Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2	- EBR
Multi-stage Alignment	- Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2	- EBR
Quick Fixes: Facepalms, Boosts	- Retrieval - EBR - L1 - Mutombo - Intermediate stages - L2	- L2



Summary by UJM and BA

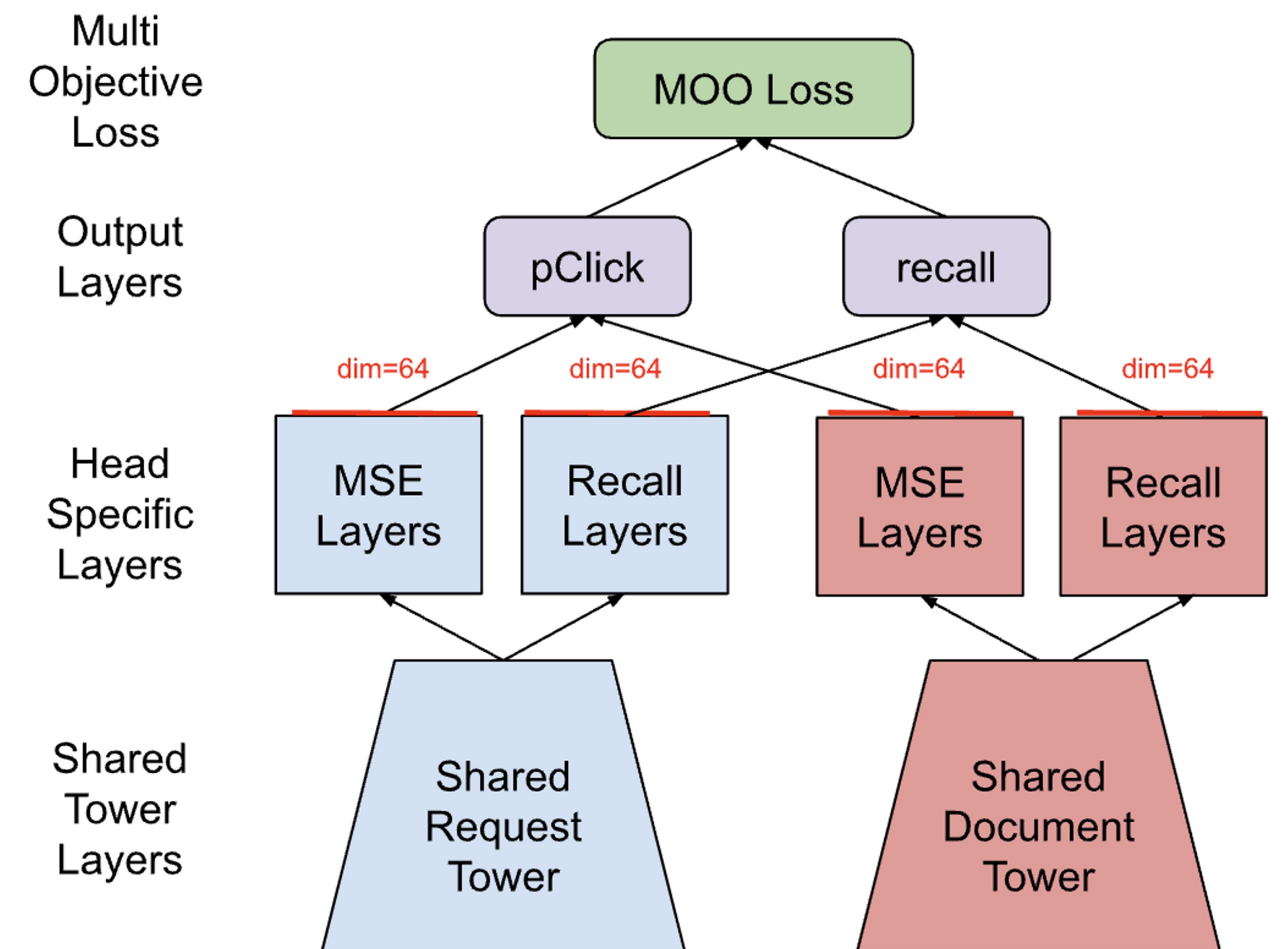
	Unified Job Marketplace	Big Auctions
# of Models	9 (ABM=6, EBR=1, L1=1, L2=1)	2 (EBR=1, L2=1)
ABM	Used for business constraints & relevance	Only used for business constraints; ABM for relevance is moved to the L2
EBR	Positive labels are seeker engagements; Negative labels are pseudo negatives; EBR scores are not necessarily calibrated	Labels are soft labels from the unbiased counterfactual big L2 auction (and supplemented with soft labels from the biased actual L2 auction); EBR scores must be calibrated predictions; Bid is used during EBR; EBR is an approximation of the counterfactual big L2 auction
Selectors	Seeker Value Selector; Poster Value Selector	Only one “Unified Selector”; EBR is an approximation of the L2 auction; Virtual bidding controls the mix of seeker value and LinkedIn value
Federation	Used for blending candidates from multi-source selectors	Not used since there is only one unified selector
L1	Quality model is merged with L1 into a multi-headed model	Eliminate L1 stage; Quality model is moved into L2; Improve EBR (faster & more accurate top k); Improve L2 (faster so can rank deeper)
L2	L2 is not monotonic	L2 is monotonic; L2 is the server request-time authority of job value; Quality model is moved to L2 (as another head); ABM for relevance is moved to the L2

GPU-based Hybrid Retrieval

Naive EBR Auction → Multi-loss → JReC → EBR MOO

- Naive EBR Auction
 - Naive auction leads to very irrelevant results due to severe *bid dominance*
 - L2 is not well calibrated, so we propose to optimize both regret and recall
- Multi-loss
 - Optimization conflict about multi-loss (-30% recall)
- JReC (Joint Optimization Recall & Calibration)
 - Inspired by JRC, we proposed JReC and achieved +10% recall but still not good enough
- EBR MOO (Multi-Objective Optimization)
 - MOO formula similarly as L2 oCPC and proved to be able to optimize two objectives efficiently
 - Next step is to add LLM based relevance objective

$$S = w_1 * pClick * bid + w_2 * S_{recall}$$

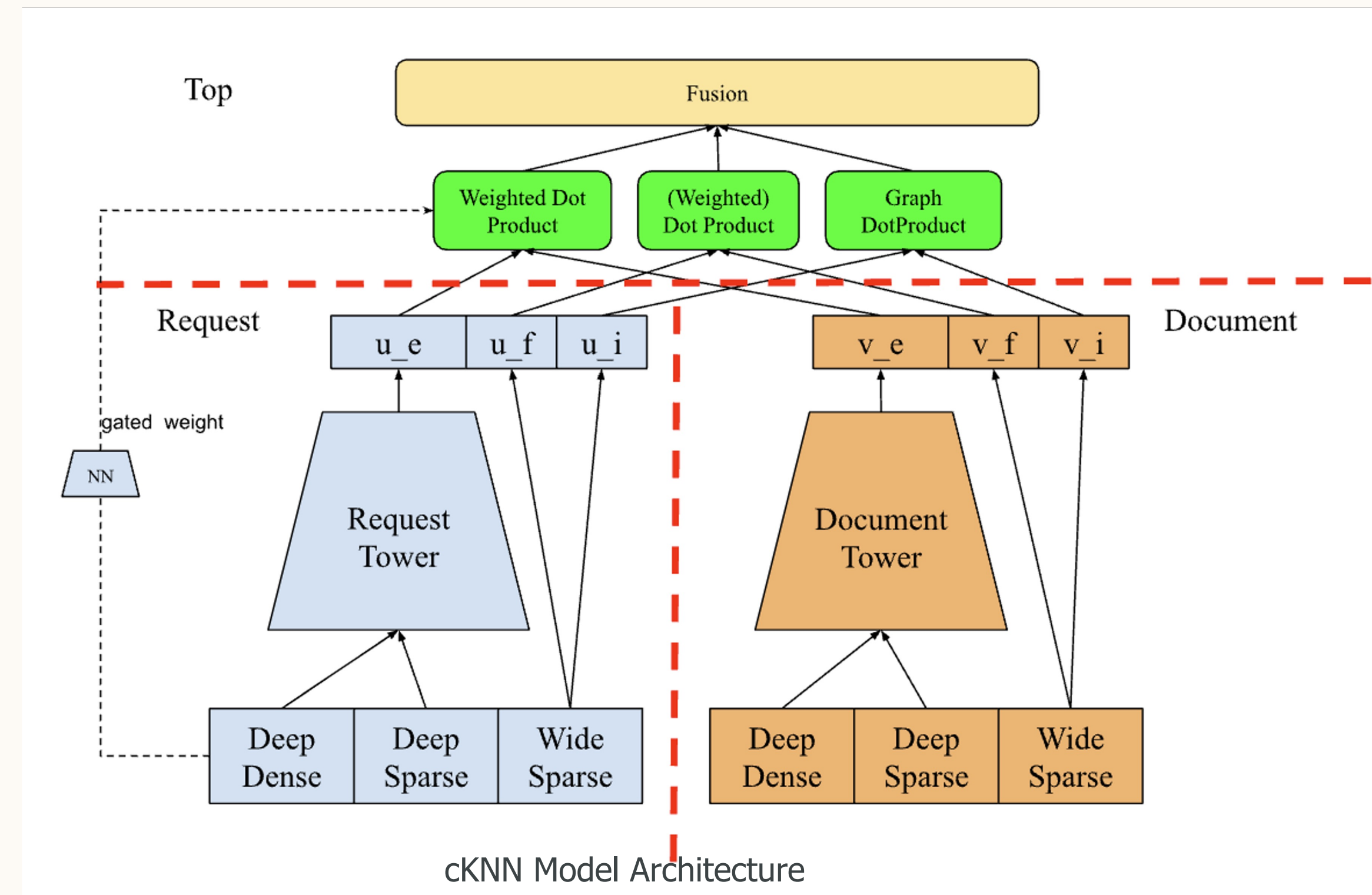


EBR MOO Model Arch and Scoring Formula

GPU-based Hybrid Retrieval

With recent launch, we achieved around +20% batch-recall@1 lift

- **Feature Engineering**
 - Evaluated 80+ features +5.4% batch-recall@1.
 - Further feature engineering + BERT +3.2% batch-recall@1.
- **Data Engineering**
 - An artificial counter-factual data pipeline to include non-impression negative +6.2% knn-recall@1k.
- **Model Architecture**
 - EBR MOO
 - Customized KNN (cKNN) goes beyond classic EBR two tower model +6.91% batch-recall@1.

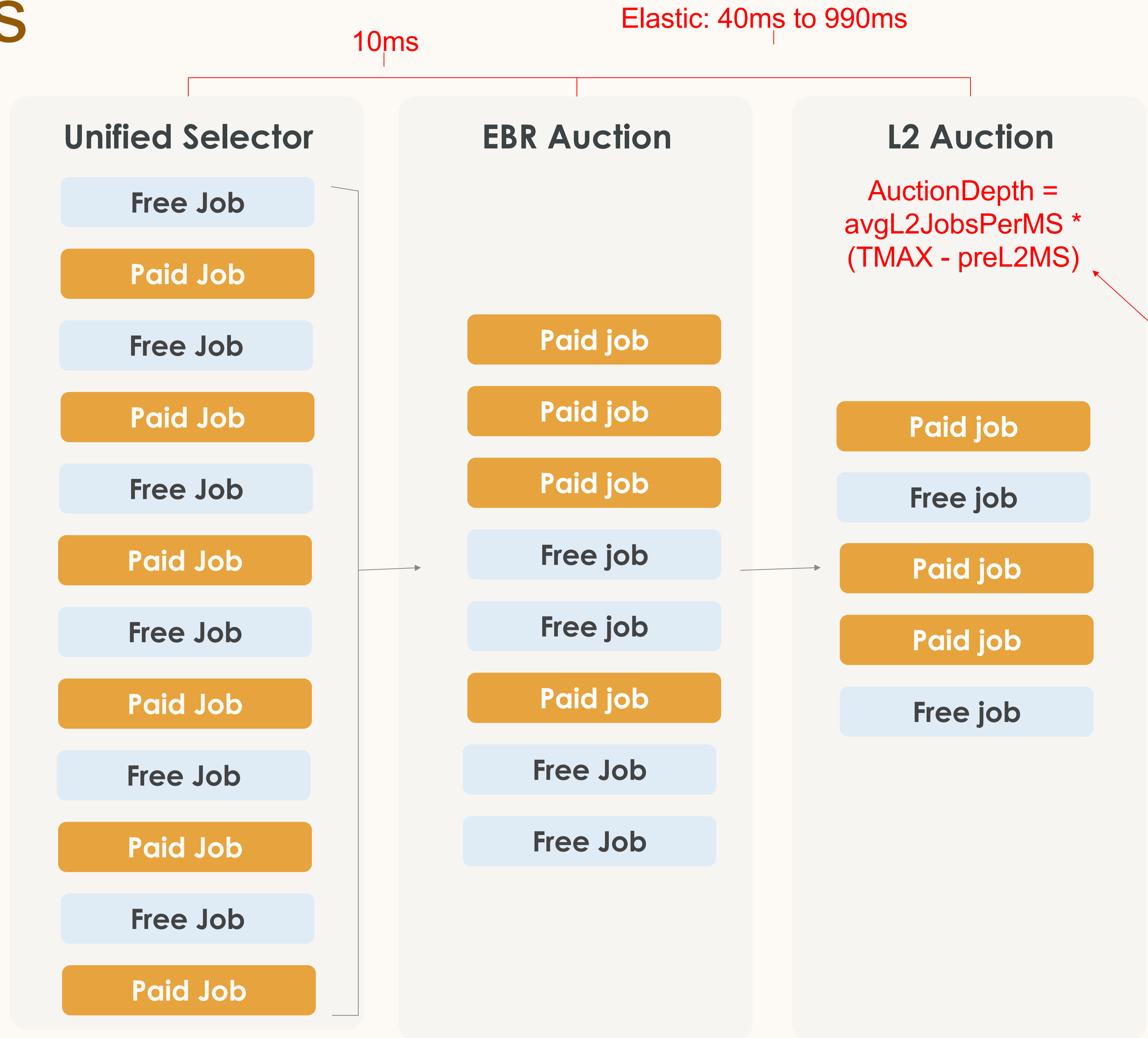


GPU-based Hybrid Retrieval

- A weighted-KNN to allow KNN with business logics.
- Near real-time updates
- 10ms retrieval latency for 15M to 2K jobs

- Revenue: +8.85%
- Bad Matches: -12%
- Qualified Applications: +10%

Big Auctions



Deeper Auction
(1000 jobs at P95)
= Marketplace
Value Generation



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We received 34,000 member verbatims between Jan. 1 and Feb. 25

from one entrypoint on Job Search web

Managing Director
Endeavor Turkey

It knows I am 45 years old, knows everything about my career. Yet this is the "job pick" it has for me: an internship for college seniors!

Inkompass Turkey Internship Program - 11 Months (General Application)
Philip Morris International · Istanbul, Turkey (Remote)
Actively recruiting

neurosurgeon

Family Physician
Access Health Care Physicians LLC · Inverness, FL
2 weeks ago · 2 applicants

Honestly in the era of AI the job search utility is the worst I have ever seen! I asked for "neurosurgeon" and I get flooded with, urology, ophthalmology, orthopedic surgery, anesthesiology and nursing jobs.

You listed a job for an optometrist and said it matches my profile, but I'm not a fucking optometrist! What the fuck is going on at linkedin?

vice president operations

Owner Operators - Flat/Step/Van
JobsInLogistics.com · Manor, TX
4 days ago · 0 applicants

Why are you showing hourly jobs & truck drivers for a VP of Ops search?

graphic design

Starbucks Barista
Safeway · Cupertino, CA
Reposted 20 hours ago

I have so much beef with the LinkedIn job searching algorithm

Head of Innovation
Amazon Web Services

LI has what, 15-20 yrs of my data & engagement...Paid jobs are ruining LI

Nightfill Manager - Coles Supermarket - Hornsby
Coles Group · Hornsby, New South Wales, Australia (On-site)
Promoted · 1 applicant

music

Supervisor de turno
AutoZone · Sacramento, CA
1 day ago · 2 applicants

I search for "music" and 30 different jobs come up for AutoZone.

retail systems director

Director, Product Management
NCSA College Recruiting · United States
1 month ago · 12 applicants

Not sure why your system cannot distinguish a set of words or a job title instead of just returning individual word results?????

religion

Task Associate
Ulta Beauty · Lewisville, TX
Reposted 2 weeks ago · 6 applicants

It's all duplicates of promoted jobs....there's hundreds and hundreds of promoted positions from 'Varsity Tutors' which is not helpful at all and basically renders the job search function useless.

museum

Data C TransPe
Reposted

Almost all of years of experience filtered by en

Poor jobs relevance makes members lose trust in us and leave

LinkedIn is incompetent

LinkedIn just cares about making money with promoted jobs

Premium isn't worth it anymore

I found a better way to find jobs elsewhere

nearly every day I get job alerts to apply for these ridiculous roles which are a) fake jobs to farm user details b) apparently not against your TOS despite reporting all of them. Is this what LinkedIn Premium is good for?

I do not have a PhD but LinkedIn says I'm a top applicant for a Professor job, in a University!!!

i'm looking for IT software and coding jobs it's showing sales

None of these specifically f

I don't need retail jobs. I am an urban planner not a shelf stocker. Half of these jobs are for a 16 year old.

coffee shop manager

Assistant Store Manager
Family Dollar · Wilmington, DE
1 week ago · 0 applicants

Why would a Family Dollar job come up. Your job search system is awful, LinkedIn.

The first few pages of this search come up with developer jobs from EPAM Anywhere - not remotely close to the search query

I don't speak recommend speakers.

"I am a CLINICAL SOCIAL WORKER! NOT A CEO, NOT A GARDNER ETC"

r/linkedin 10 days ago
I simply can't fathom how bad LinkedIn's job search function is
"Media" as a keyword = 170 results
"Social Media" as a keyword = 126,290 results
"Social media marketing" as a keyword = 190,748 results
"Media marketing" as a keyword = 0 results
WHAT
767 ↓ 65 ↑

If I had to guess, I'd bet that they weren't getting enough hits when recruiters paid to promote their posts, so they kept expanding the reach over and over again, and now there's not even a thin connection to our searches anymore. The worst mismatches are all tagged as Promoted. Seems like a vain attempt to increase promotion revenue, at the expense of making the site totally unusable for one of its core, basic functions. Dumb, short sighted decision in my opinion.

Owain-X · 2d ago
LinkedIn DOES NOT CARE. They earn more revenue from these companies than from any personal subscriptions. I cancelled my premium after getting jobs via email and in web results from the same company every day. A company that when you click their apply link tells you there is no role and they are a "talent community". Over a dozen reports and two conversations with LI support. Zero change. We're the product not the customer when it comes to LI.

TheWatch83 · 11d ago
Use google "site:LinkedIn.com" for results.
TheBardOfAbe1 · 11d ago · Edited 10d ago
Use Clay.com - they have LinkedIn Job search option that is for reason unknown INSANELY much better than LinkedIn's own search results.
For a simple job search I put in Clay just job position names, location and put 30 days from posting (or 14 days, or 7 days) depending how "fresh" jobs I want to check.
ALL OF THE RESULTS ARE ACCURATE.

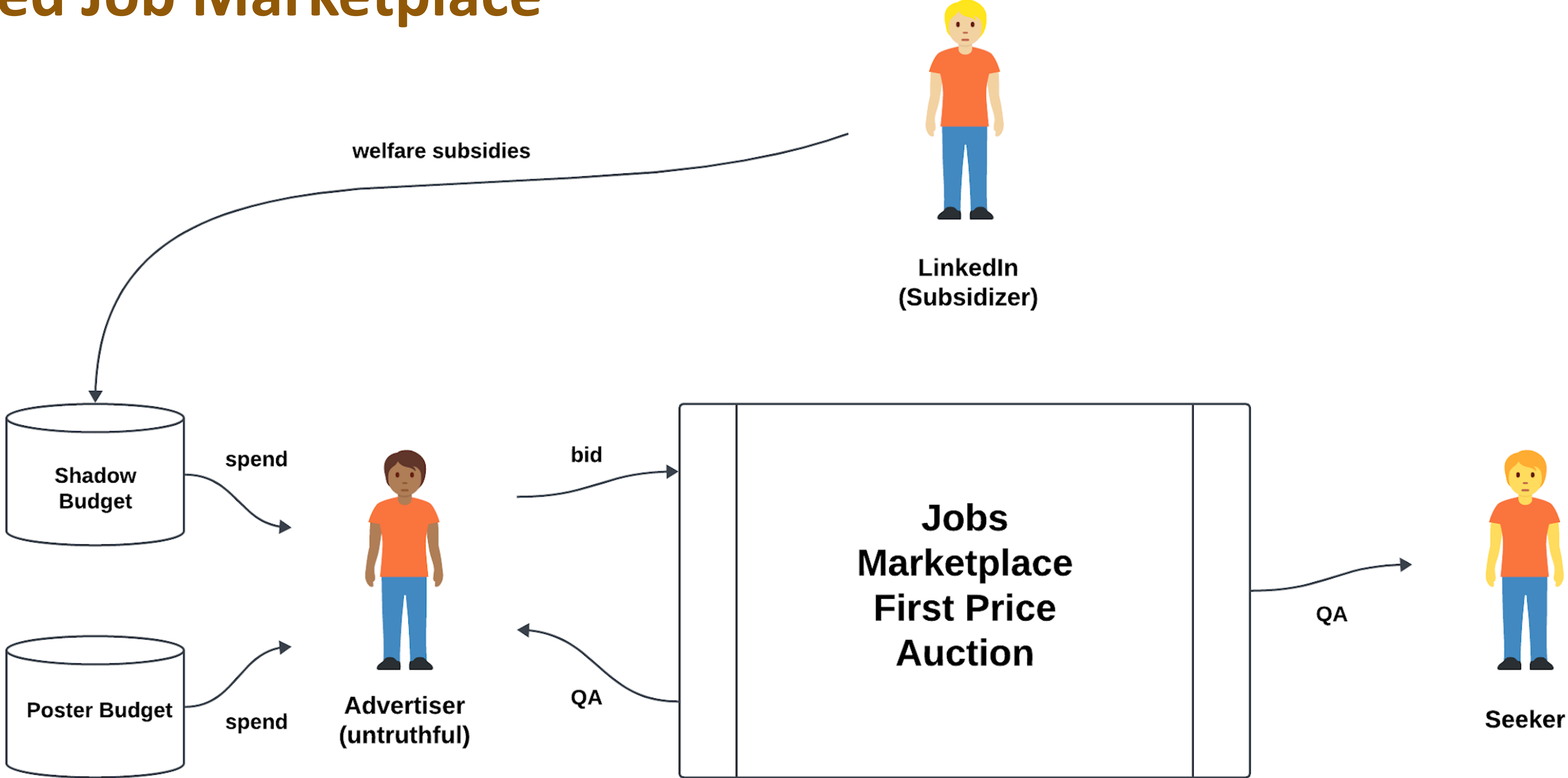
Karol Jedrzejewski @KPJedrzejewski
I'm honestly surprised at how bad LinkedIn search engine is considering how the platform is. @LinkedIn I don't want your AI resume assistant - take my money and remove irrelevant sponsored jobs. Do you know any LinkedIn jobs wrapper or alternative?
#LinkedIn #Jobs #Careers

Kenneth Hazlett @KennethHazlett
I found a way to get rid of the stupid promoted jobs on LinkedIn. Get the ad blocker uBlock Origin and copy and paste the following into the "My filters" section:
linkedin.com##li:has-text(Promoted)
Now filter most recent jobs. Your welcome.

Eduardo Soliz @edsolizvoice
I'm pretty close to being done with @LinkedIn. Their job search sucks. Clicking "Do not recommend this job to me anymore" apparently does nothing, so I keep getting the same jobs recommended that I didn't want the first time. It's also just oozing with toxic positivity.

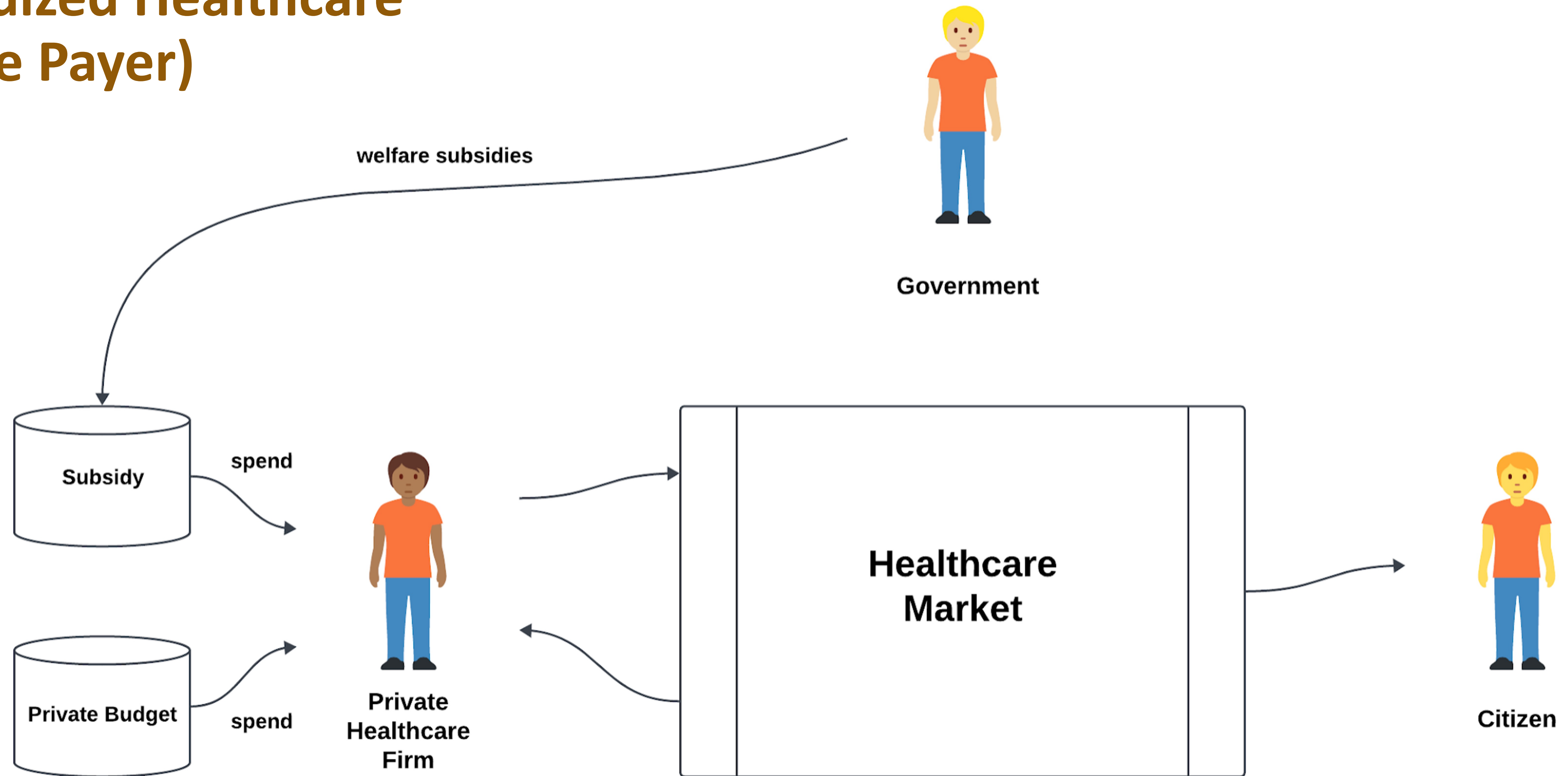
Harpreet Vishnoi @VishnoiHarpreet
@Glassdoor >>> LinkedIn (Job listing experience)
LinkedIn populates the job listing with promoted jobs on top. Jobs which I applied for 1 month back are still on top. This ruins my ux since I have to do more manual effort.

Unified Job Marketplace



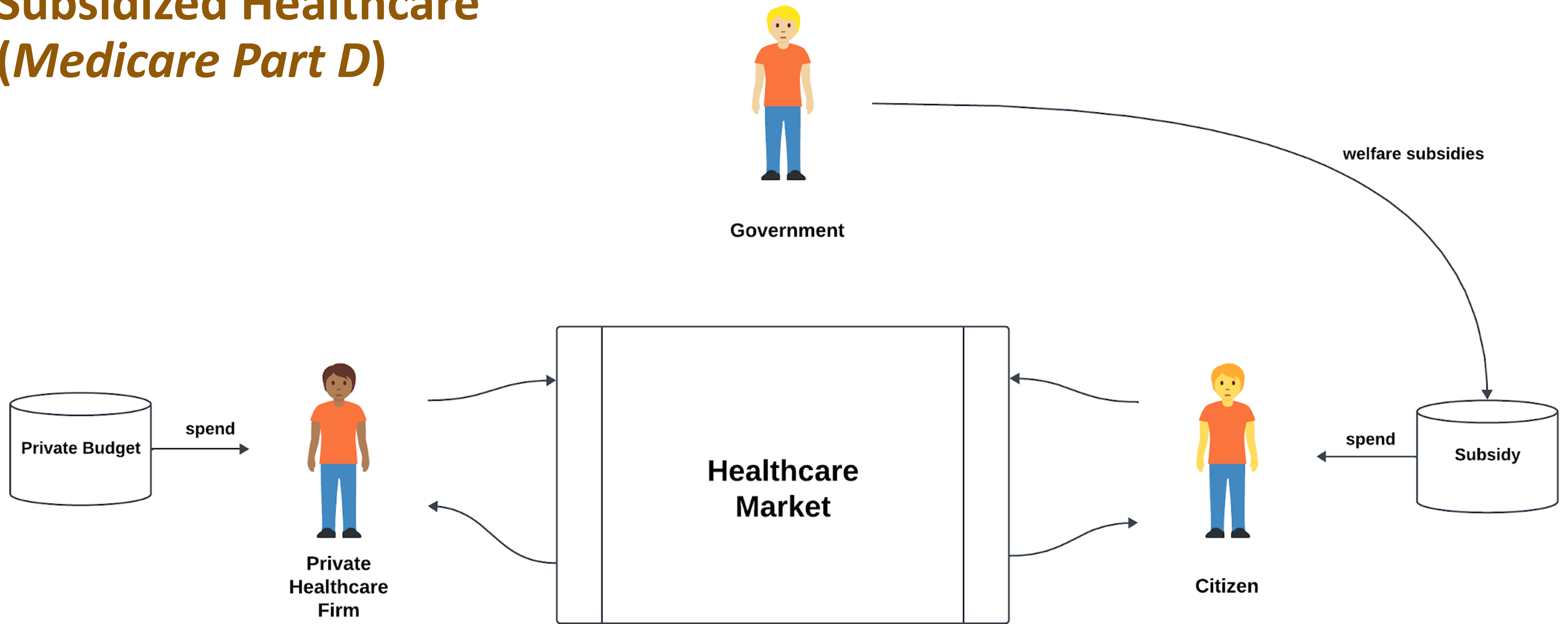
By giving the welfare subsidies to the advertisers, we are encouraging an increase in bid dominance & decrease in relevance.

Subsidized Healthcare (Single Payer)



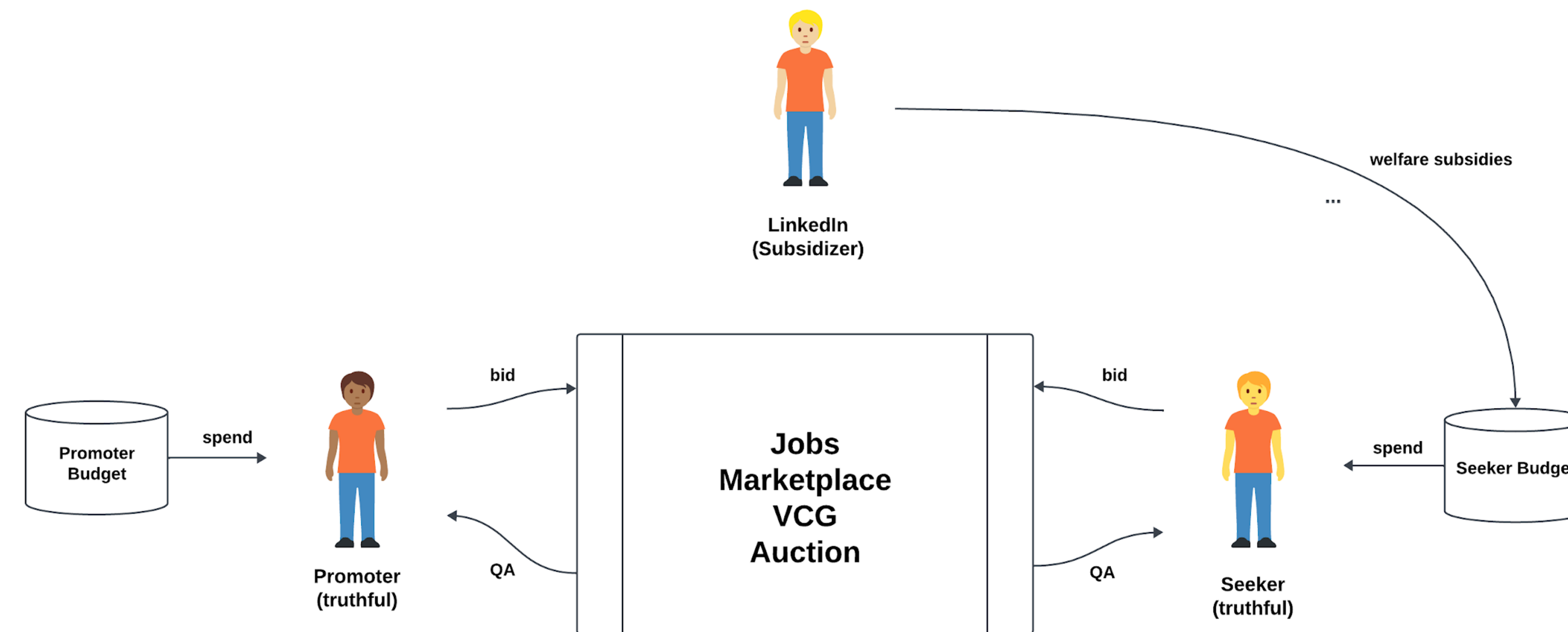
By giving the welfare subsidies to the private firms, a *perpetual “raise-the-subsidy” incentive* occurs to keep citizen welfare from dropping.

Subsidized Healthcare (Medicare Part D)



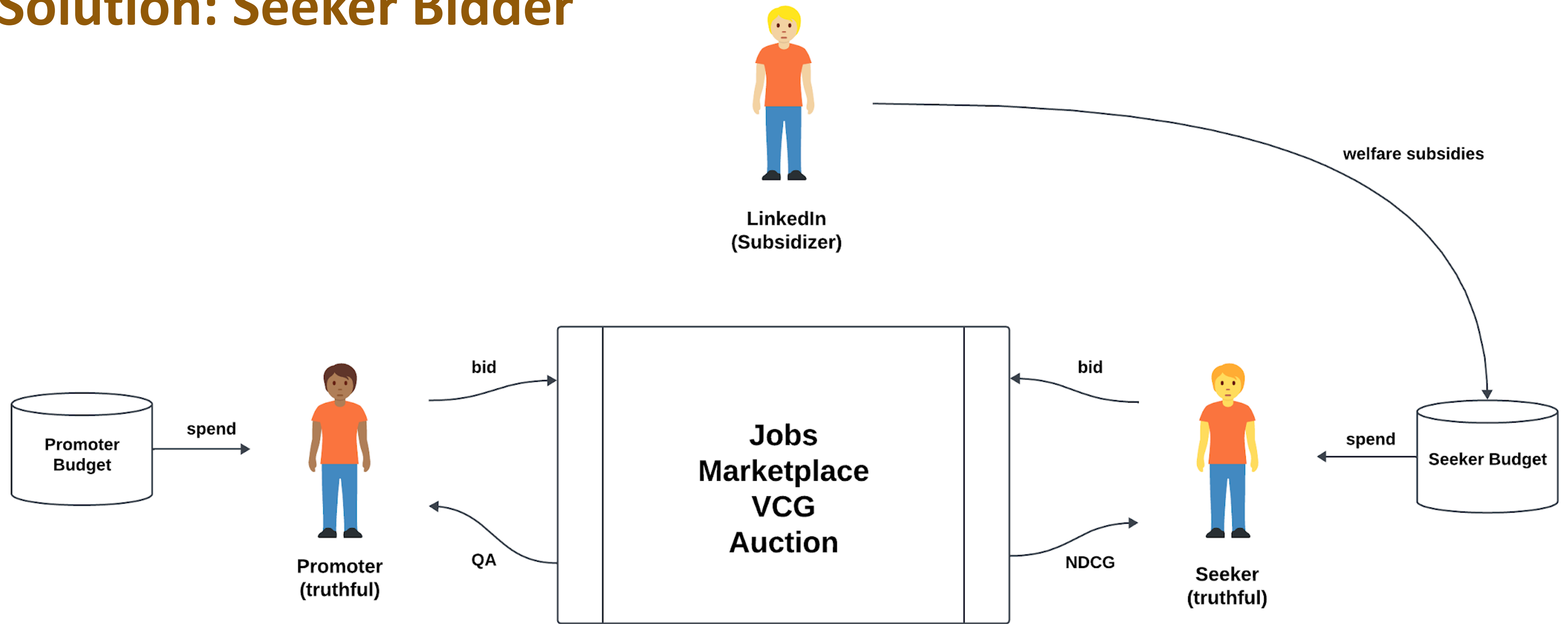
By giving the welfare subsidies to the healthcare seekers, the *perpetual “raise-the-subsidy” incentive* does not occur.

Seeker Budget Caps



- Finite seeker budget caps are one mechanism to limit seeker value to optimize I2P.
- However, calculating seeker budget caps requires forecasting seeker behavior for the next 24 hours.
- Is there an alternative for controlling I2P with using a seeker budget cap?
- Yes, and it has existed for decades.

Solution: Seeker Bidder




By giving the welfare subsidies to the seeker, bid dominance is dramatically reduced, and therefore relevance is dramatically increased & long-term revenue is maximized.

Why Seeker Bidding & Boosting vs Shadow Budgets?

- Main reasons:
 - Seeker bids are more efficient at optimizing seeker value/LTV than shadow budgets.
 - The dominant bidding strategy for the seeker is to uniformly bid their constant true value for relevance times the expected relevance contribution of a job. Any other bidding strategy either leaks unnecessary free value, or leaks unnecessary seeker value
- Sources of developer productivity benefits:
 - Auction Efficiency
 - Incentive Compatible Auction
 - Infrastructure Simplicity
 - Known Optimal Parameterization


Auction Efficiency

- An **efficient auction** allocates supply to demand in a way that maximizes overall welfare or utility.
- **Auction efficiency** ensures that the allocation achieves the best possible outcome given the available information. Serving intern jobs to executives is not an efficient auction.



George Schweitzer
Media/Mktng Advisor. Former CMO CBS. Now: Projects of Purpose. Board Member 92NY. Senior Fellow







Experience

 **CBS**
48 yrs 1 mo

- **President, CBS Marketing Group**
1995 - Apr 2020 · 25 yrs 4 mos

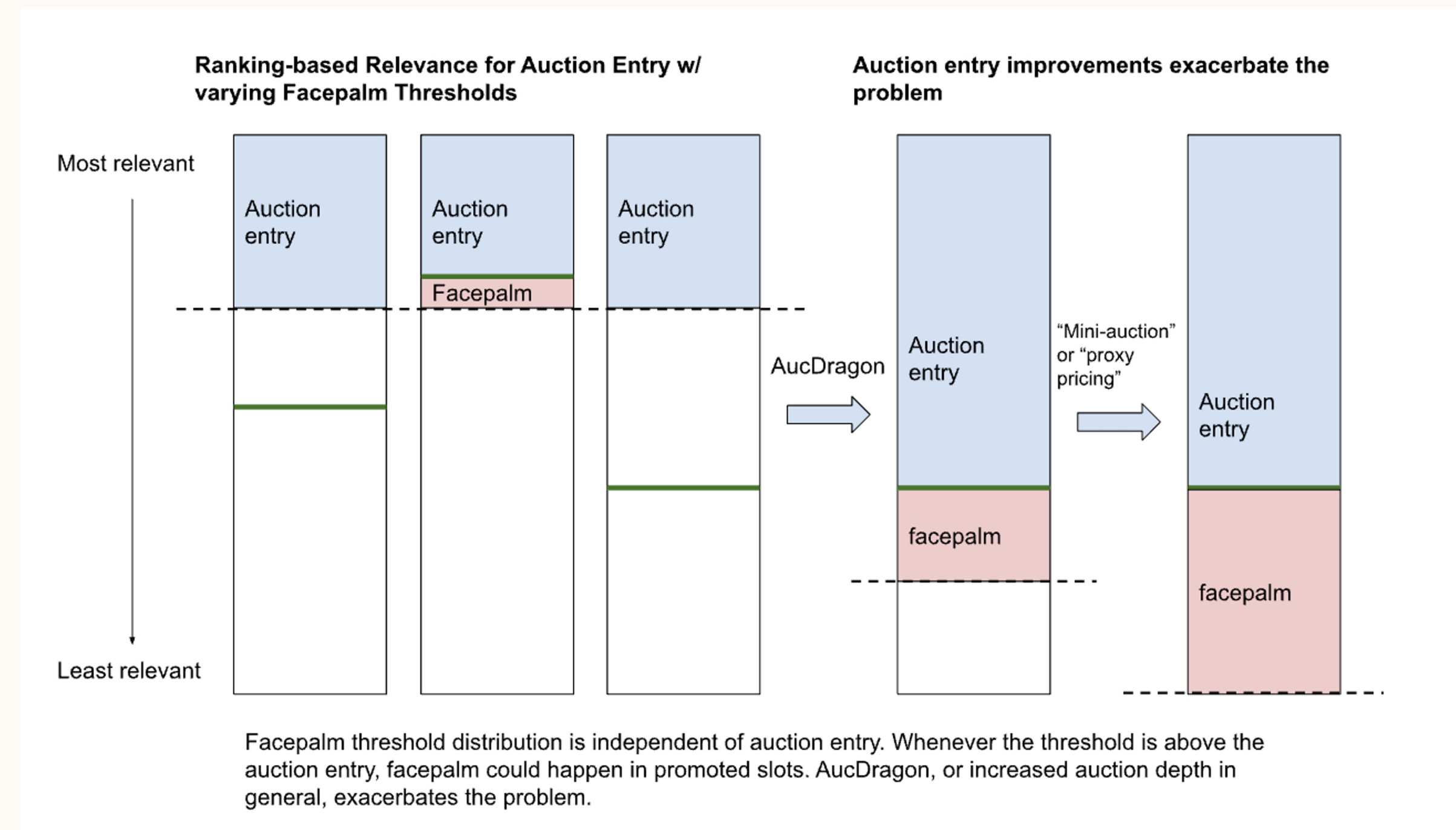
All Marketing activities for CBS -- Entertainment, News, Sports, Corporate. In short: Get people to watch!

Top job picks for you

-  **Intern, Corporate Communications**
Los Angeles Rams · Agoura Hills, CA (Hybrid)
3 connections Fast growing
-  **Intern, Public Relations– Summer 2024**
goop · Santa Monica, CA (Hybrid)
Actively recruiting Fast growing
-  **Summer Interns - Media Communications**
GreenlightGO · New York City Metropolitan Area (Remote)
Be first of 7 to apply Easy Apply
-  **Remote Vacation Booker- Part Time**
NEVER ENDING TRAVELS · Orlando, FL (Remote)
Be first of 4 to apply Easy Apply
-  **Data Entry Typist - Remote**
Seek 2 Thrive · Chicago, IL (Remote)
High skills match
-  **Retail Baseball Ambassador**
DICK'S Sporting Goods · Morgan Hill, CA (On-site)
Actively recruiting

Auction Efficiency: Competition

- **Auction efficiency** should monotonically increase as competition increases.
- *Shadow budgets* design does not have this property.
- Increasing auction depth increases likelihood of irrelevance, due to **bid dominance**.
- Irrelevance is the opposite of auction efficiency.

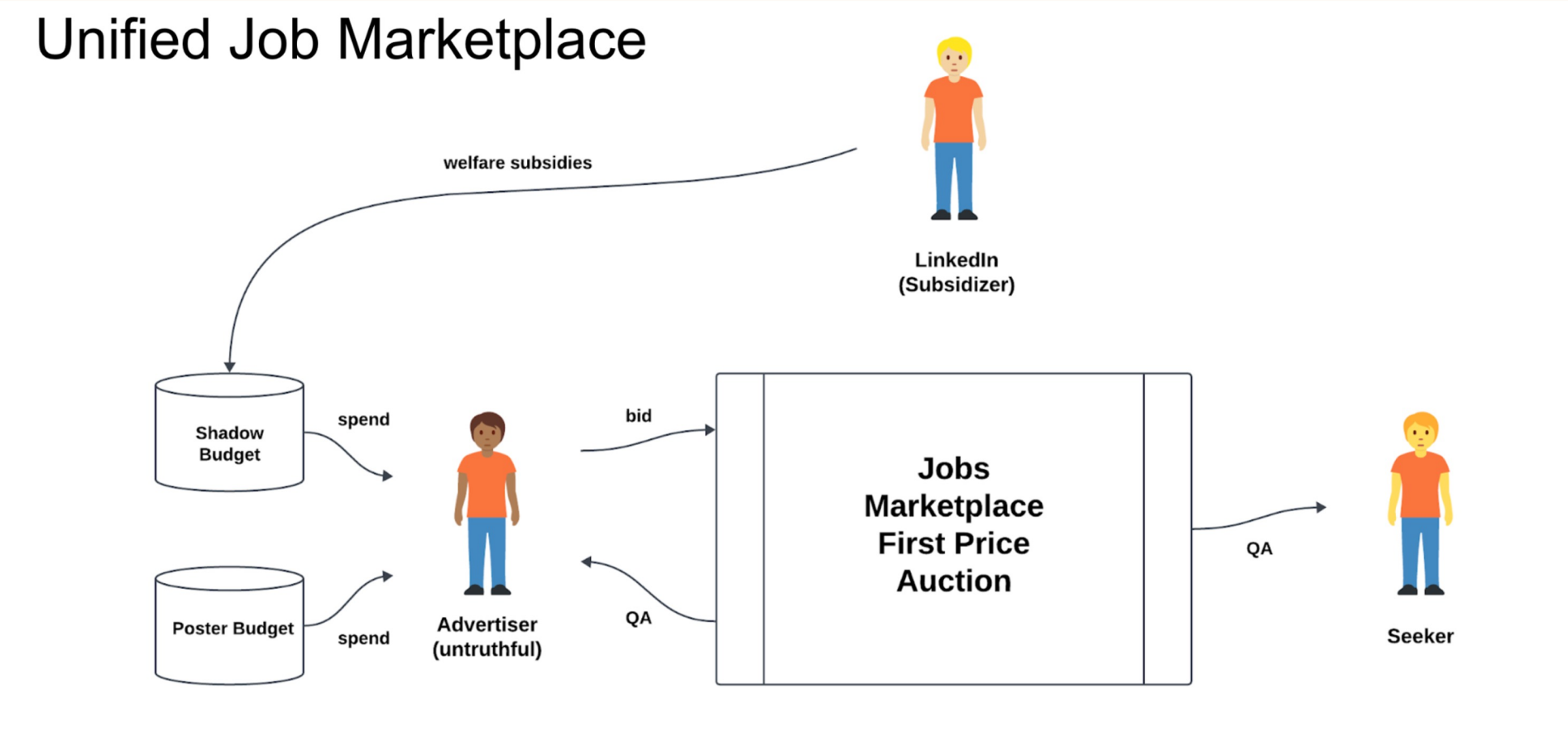


Auction Efficiency = Developer Productivity

Category	Directly Improve Auction Efficiency	Hide Auction Inefficiency Using Rules & Heuristics
<i>Models To Maintain & Optimize</i>	pApply	L1 model, jobs2x, query2x, member2x, pApply
<i>Rules</i>	None	<ul style="list-style-type: none"> - Many, complex, fragile, human curated rules - L1 threshold - L1 auction entry boost - Min & max bids - fixed ad slots & heuristic blending rules
<i>Competition (Auction Depth)</i>	As deep as latency allows	<ul style="list-style-type: none"> - Deeper degrades relevance & auction efficiency - Shallower degrades liquidity
<i>pApply Improvements Impact</i>	<ul style="list-style-type: none"> - Promoter value increases - Seeker relevance increases 	<ul style="list-style-type: none"> - Promoter value increases - Bid dominance mutes seeker relevance increase
<i>Developer Productivity</i>	High	Low

L2: Seeker Bidder MOO

Total Value = Weighted(LI Value, Poster Value, Seeker Value)



CPC:

$$\text{Auction score} = \text{paced_bid_cpc} * \text{pClick}$$

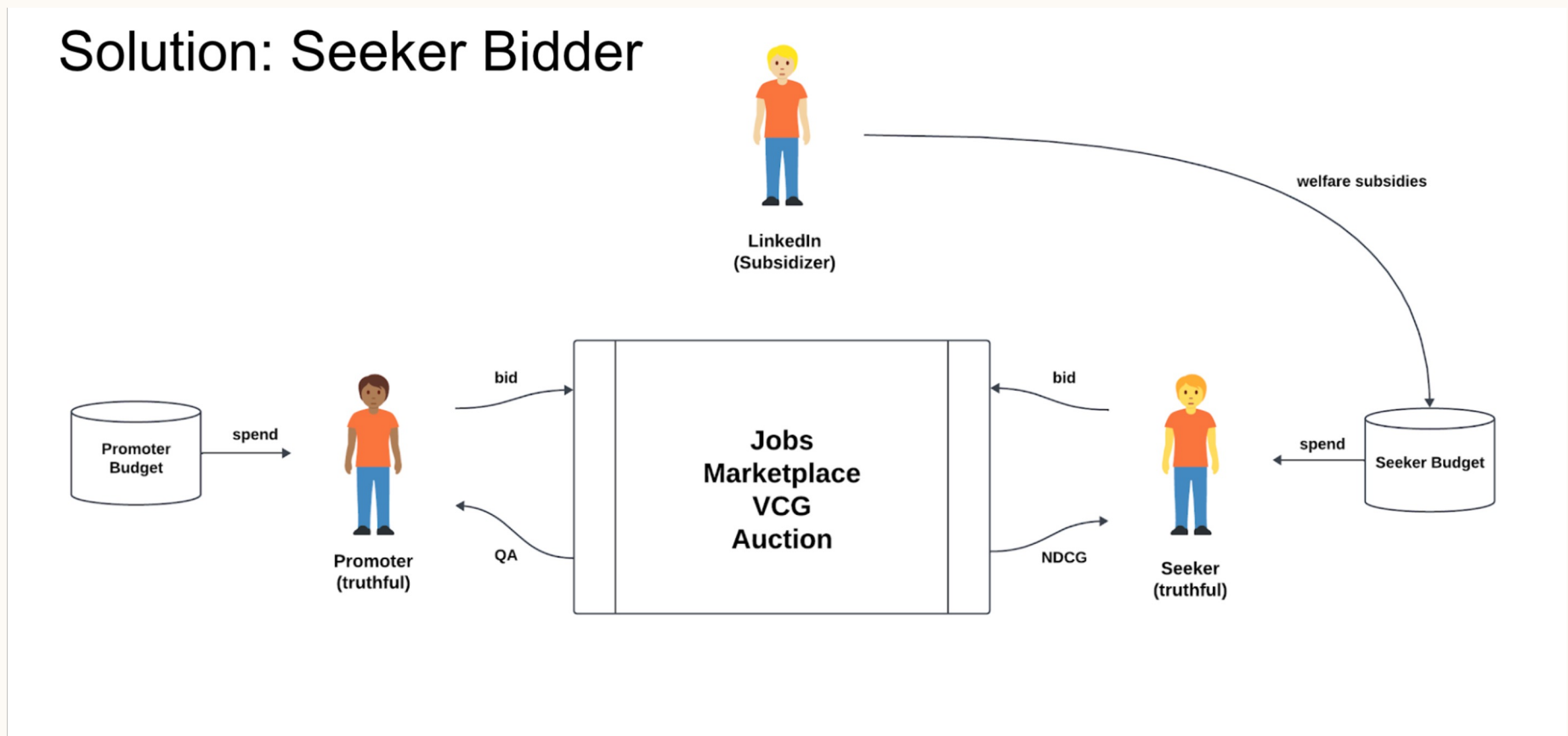
Optimized Charge Per Click (oCPC):

$$\text{Auction score} = \text{paced_bid_cpc} * (\text{pApplyGivenClick} / \text{avg_pAGC}) * \text{pClick}$$

OCPC + Seeker Bidder MOO:

$$\text{Auction score} = \text{paced_bid_cpc} * (\text{pApplyGivenClick} / \text{avg_pAGC}) * \text{pClick} + \text{seeker_bid} * \text{pClick}$$

+10% Better Matches without Revenue Tradeoffs



By giving the welfare subsidies to the seeker, bid dominance is dramatically reduced, and therefore relevance is dramatically increased & long-term revenue is maximized.



Agenda

- 1 Optimizing Hiring Outcomes – (2020-2022)
- 2 Unified Jobs Marketplace – (2022-2023/24)
- 3 Big Auction and Beyond – (2023/24 – Today)

Thank you