



**MOLOCO**

# Machine Learning and data infrastructure in Ad-Tech by Moloco

How to handle 80B+ real-time bidding everyday

# Speaker: Min-gyu Cho

## Work Experience

- Data Scientist / Head of Ad Cloud Solution at Moloco Inc.
- Assistant Professor at DGIST
- Data Science Unit Leader at 11st
- Product Manager & Big Data Strategy at SK Planet
- Associate at McKinsey & Company

## Education

- M.S. & Ph.D. in Computer Science and Engineering at Univ. of Michigan
- B.S. in Electrical Engineering at Seoul National Univ.

# Speaker: Daeseob Lim

## Work Experience

- Technical Program Manager at Moloco
- ML software engineering for VOD streaming & IPTV solutions at Castis.



## Education

- Ph.D. candidate in Brain & Cognitive Sciences at Seoul National Univ.
- M.S in Computer Science at Univ. of California, San Diego
- B.S. in Computer Engineering at Seoul National Univ.

# Today's Agenda



# Ad-tech 101



# **Ad-Tech?**

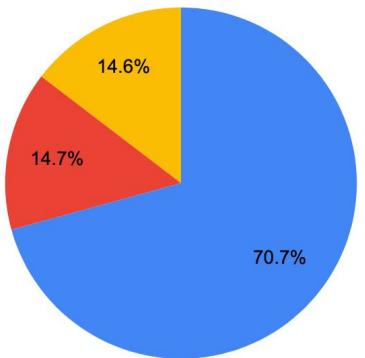
Advertising + Technology

# Why do I need to pay attention to ad-tech?

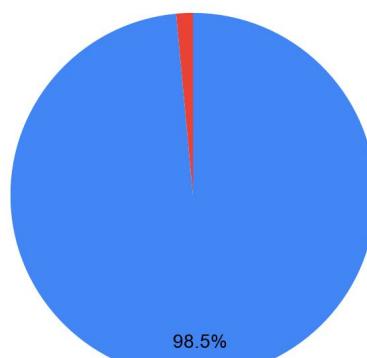
Advertising is the main revenue source of tech giants

 Advertising Revenue

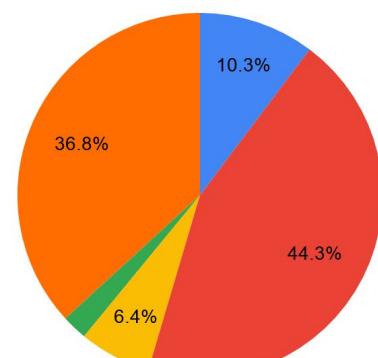
Google Segment Revenue (2018)



Facebook Revenue (2018)



Naver Revenue (2018)



● Google properties revenues   ● Google Network Members' properties revenues  
● Google other revenues

● Advertising   ● Payments and other fees

● 광고   ● 비즈니스플랫폼   ● IT플랫폼   ● 콘텐츠서비스   ● 라인및기타플랫폼

# What is advertising?

**“Advertising** is an audio or visual form of *marketing communication* that employs an openly sponsored, nonpersonal message to *promote or sell a product, service or idea.*” - Wikipedia



Needle shop ad  
From Song dynasty,  
China (1,000+ years ago)



Coca-cola ad  
from 1890

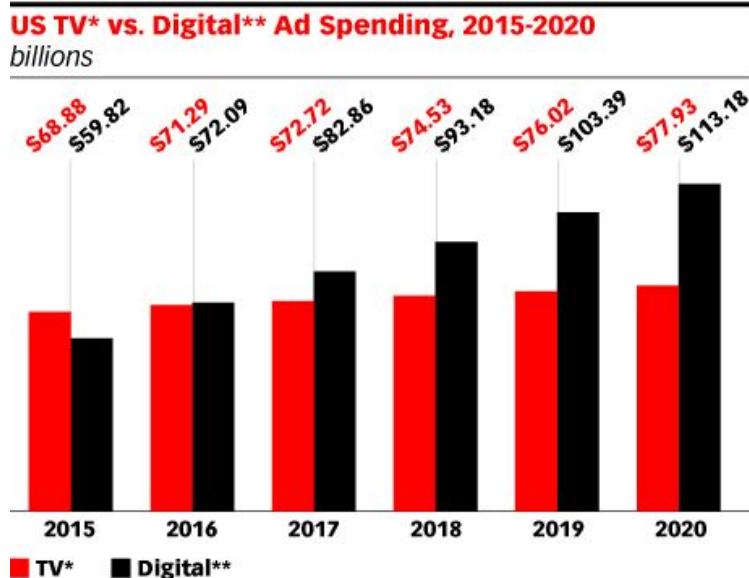


TV ad



Digital ad

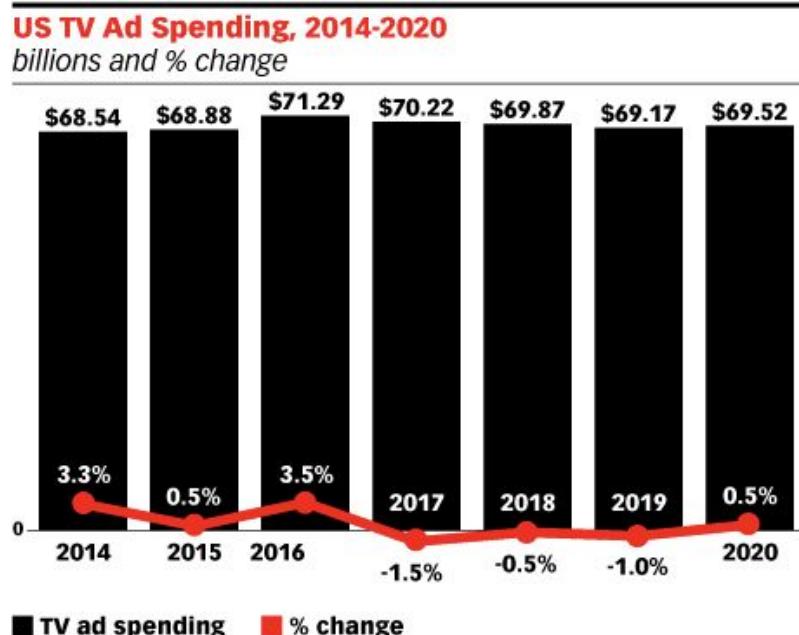
# Digital is eating the advertising market



Note: \*includes broadcast TV (network, syndication and spot) and cable TV;  
\*\*includes advertising that appears on desktop and laptop computers as well as mobile phones, tablets and other internet-connected devices, and includes all the various formats of advertising on those platforms  
Source: eMarketer, Sep 2016

215529

www.eMarketer.com

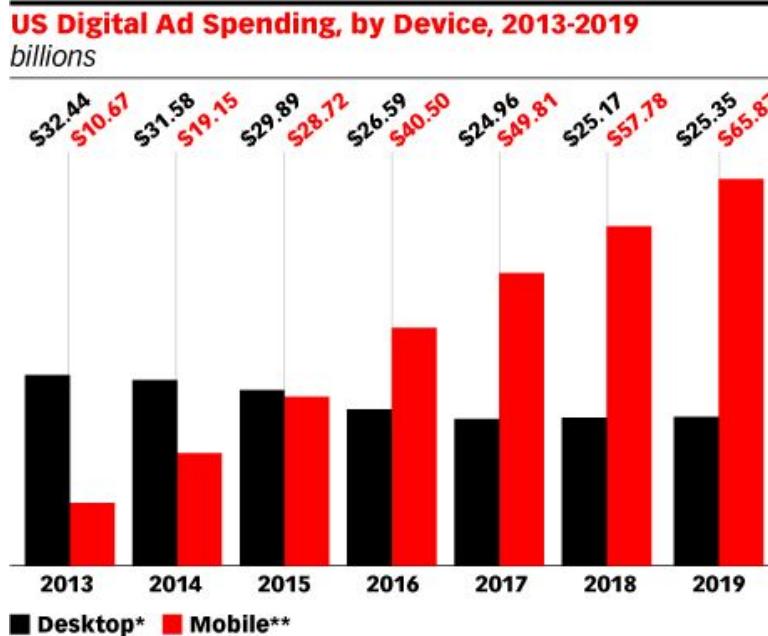


Note: excludes digital  
Source: eMarketer, March 2018

236231

www.eMarketer.com

# Mobile & programmatic is eating the digital ads market

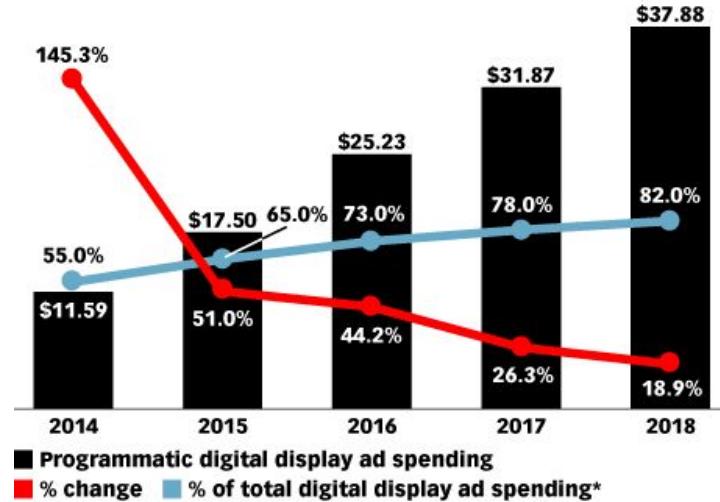


Note: \*includes spending primarily on desktop-based ads; \*\*includes classifieds, display (banners and other, rich media and video), email, lead generation, messaging-based advertising and search; ad spending on tablets is included

Source: eMarketer, March 2015

186555

[www.emarketer.com](http://www.emarketer.com)



Note: digital display ads transacted via an API, including everything from publisher-erected APIs to more standardized RTB technology; includes native ads and ads on social networks like Facebook and Twitter; includes advertising that appears on desktop/laptop computers, mobile phones, tablets and other internet-connected devices; \*includes banners, rich media, sponsorship, video and other

Source: eMarketer, Sep 2016

215870

[www.emarketer.com](http://www.emarketer.com)

# What is programmatic ads?

## What is programmatic ad buying?

... the use of *software* to purchase digital advertising, .... It's using machines to buy ads, basically.

## Why does programmatic advertising matter?

*Efficiency.* ... ... Programmatic advertising technology promises to make the ad buying system more efficient, and therefore cheaper, by removing humans from the process wherever possible. ...

Source: <https://digiday.com/media/what-is-programmatic-advertising/>

# So what problem do we have?



Winning ad  
is served  
at user's device

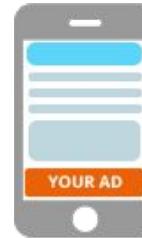


Auction is over  
at exchange

*bidrequest* is born  
when user opens an  
app



Bidders make bids



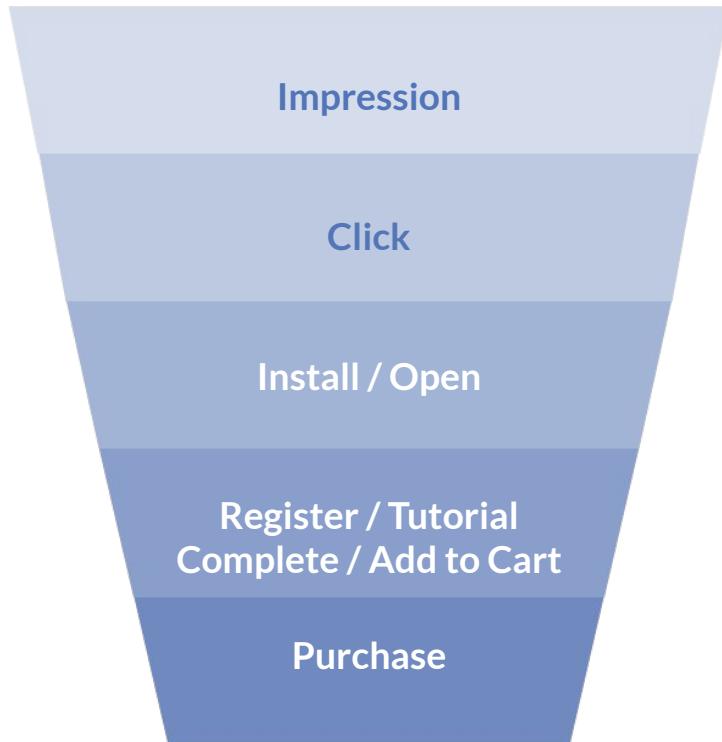
Exchange  
broadcasts  
*“bidrequest”* to  
potential bidders



# What is the goal of the advertiser?

Advertisers want user to reach further in the marketing funnel, e.g.,

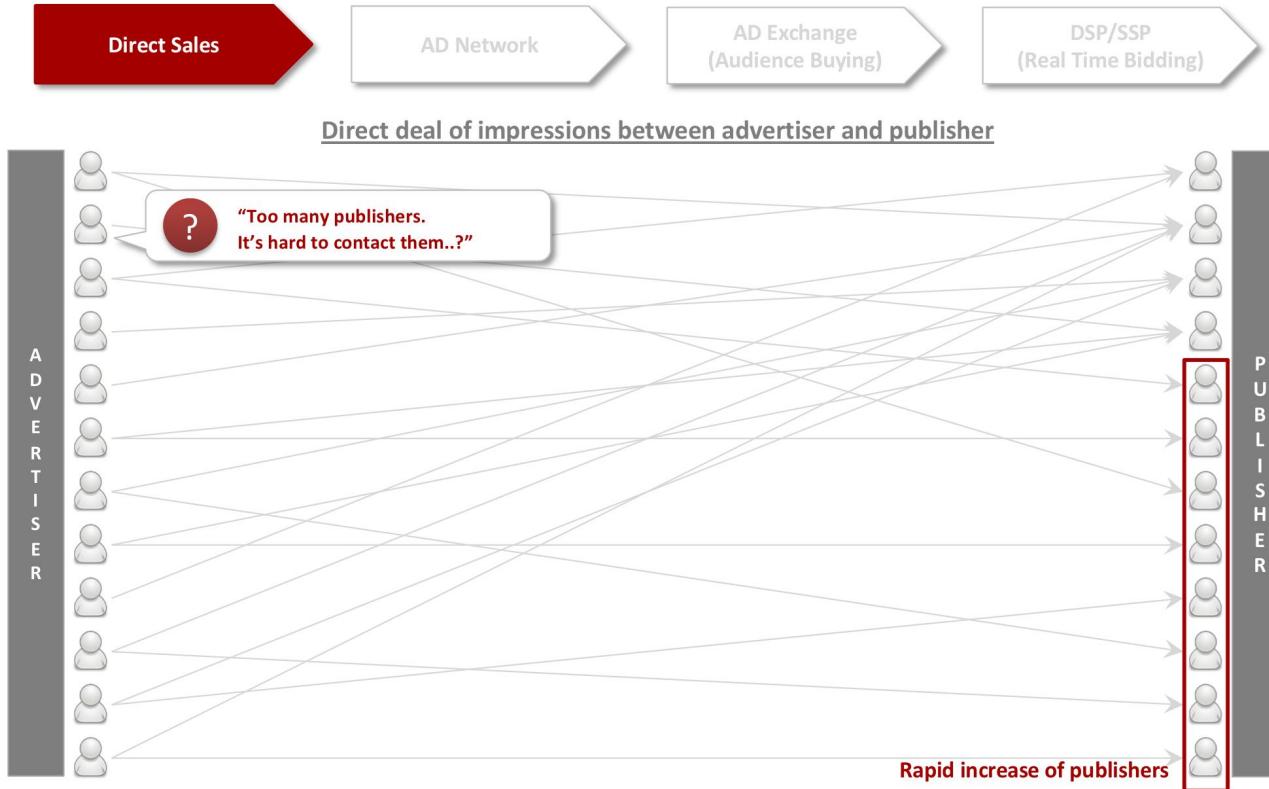
- Awareness of their applications/services
- Response to advertising
- Install
- Retention
- Purchase



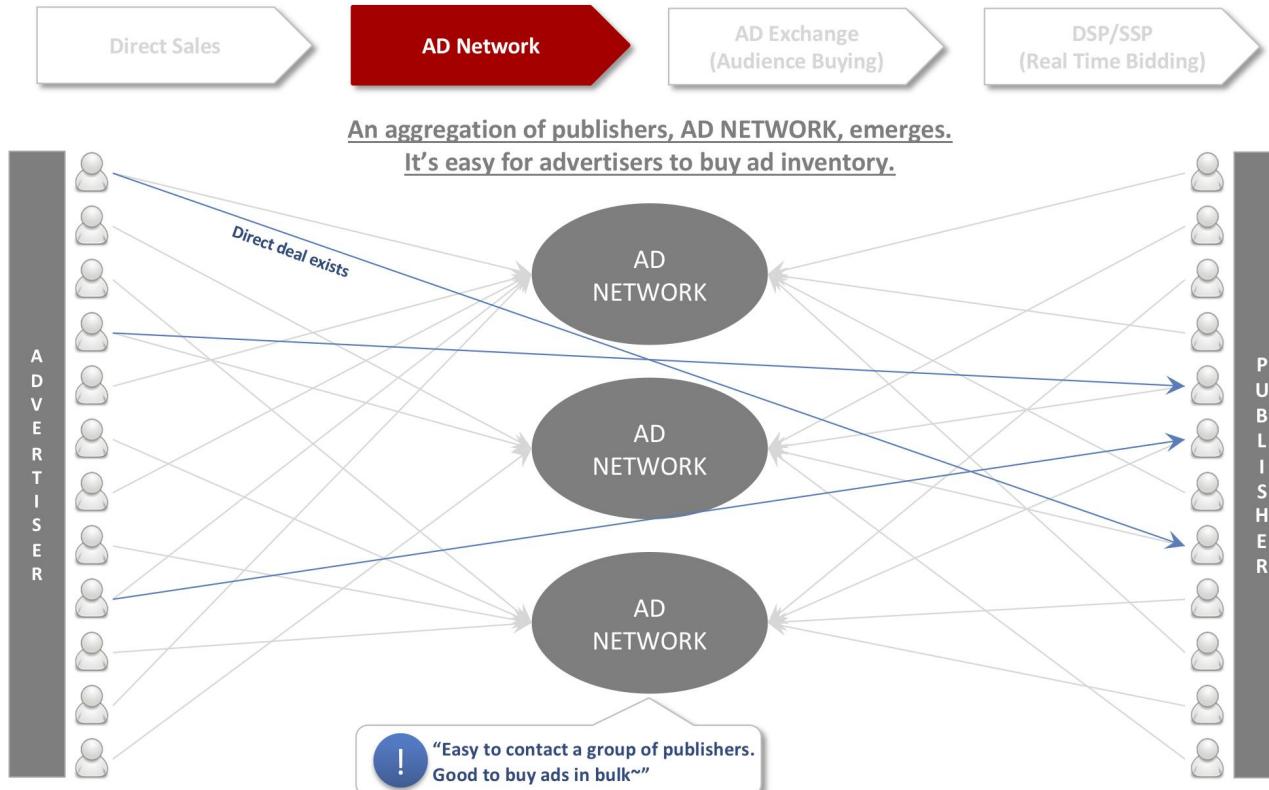
# **Evolution of Digital Ad Platform**

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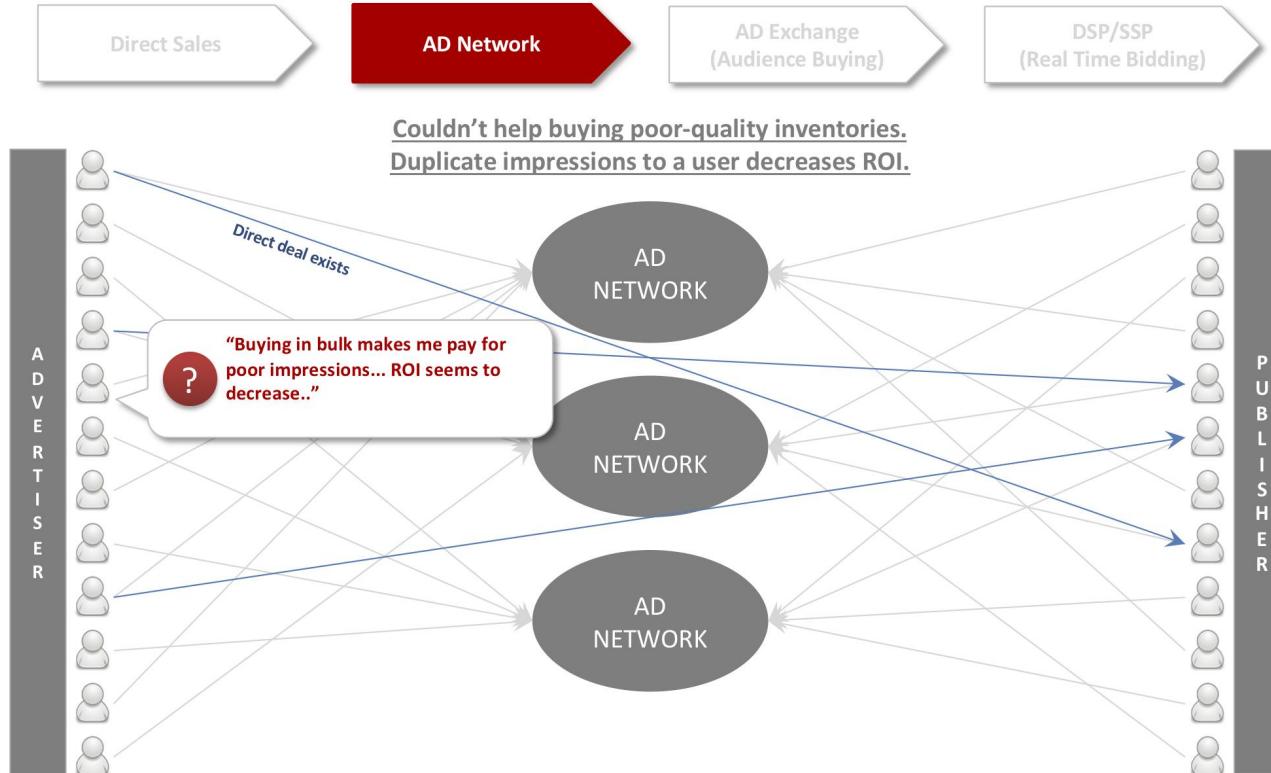
# Evolution of digital ad platform: direct sales



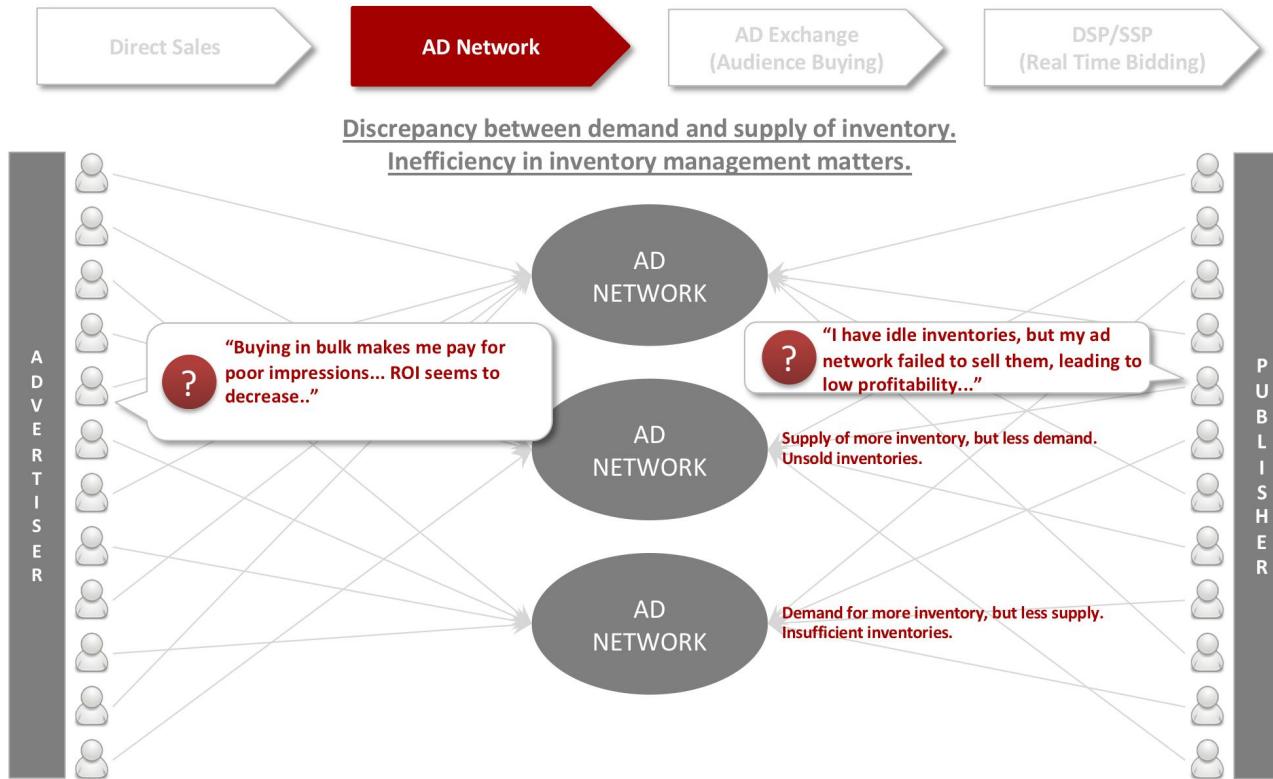
# Evolution of digital ad platform: ad network (1/3)



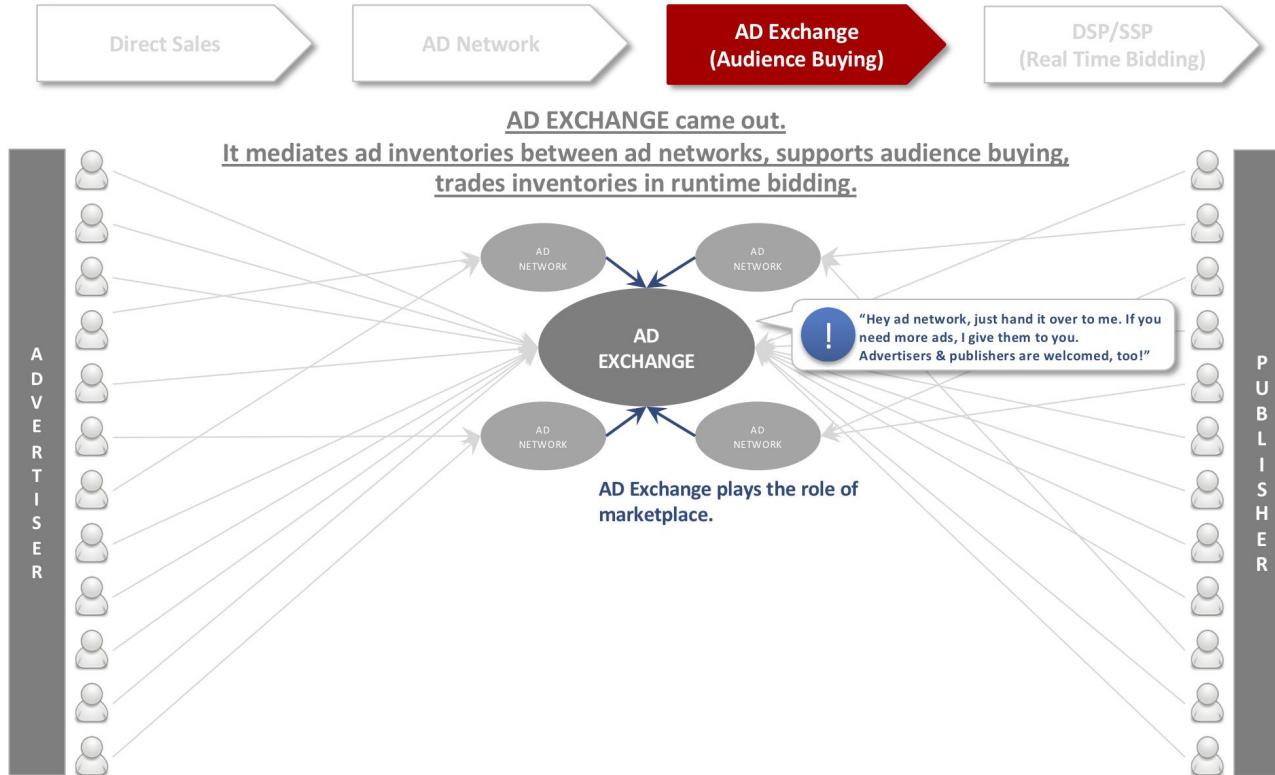
# Evolution of digital ad platform: ad network (2/3)



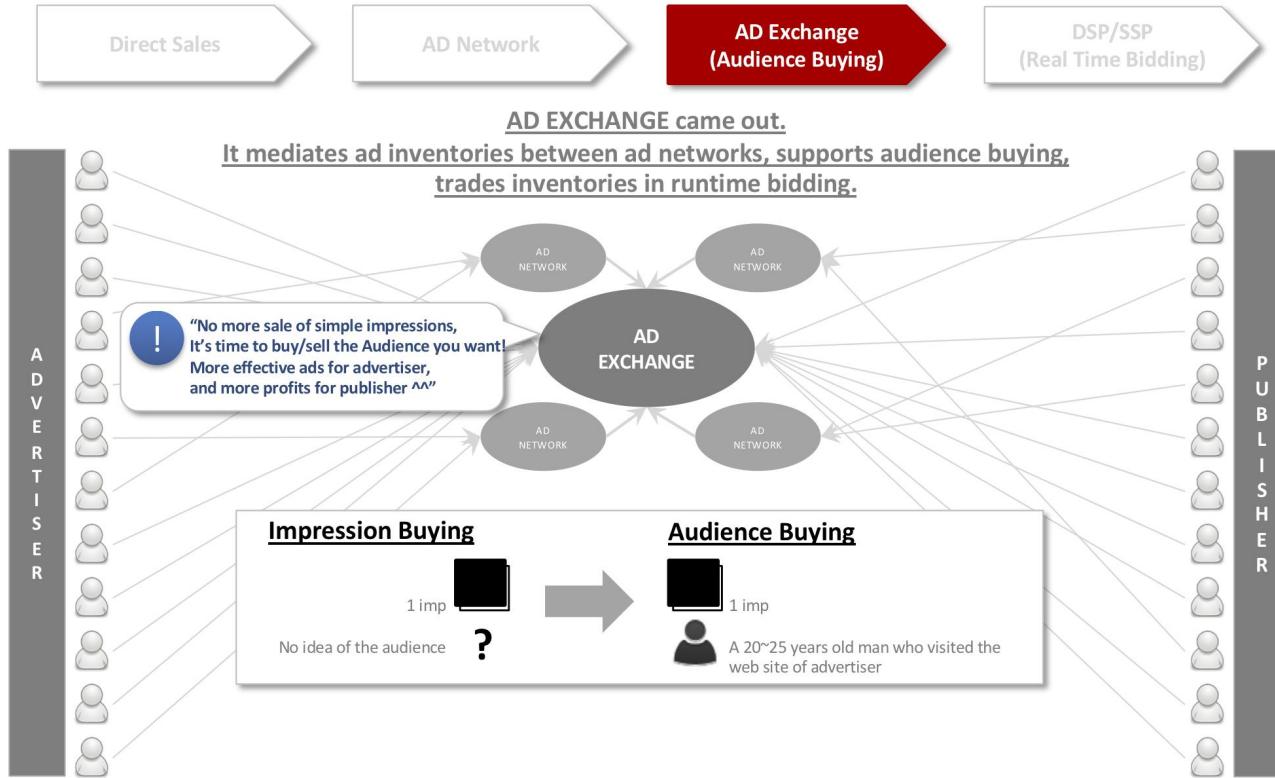
# Evolution of digital ad platform: ad network (3/3)



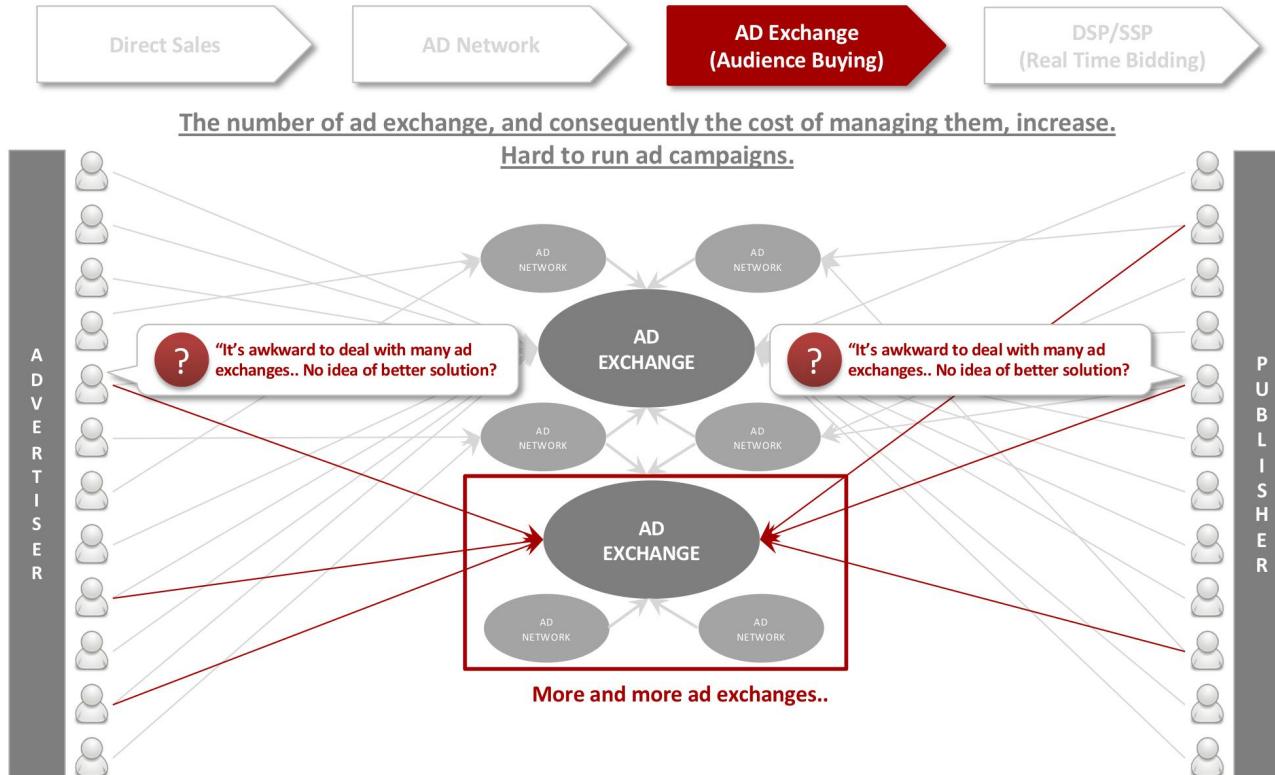
# Evolution of digital ad platform: ad exchange (1/3)



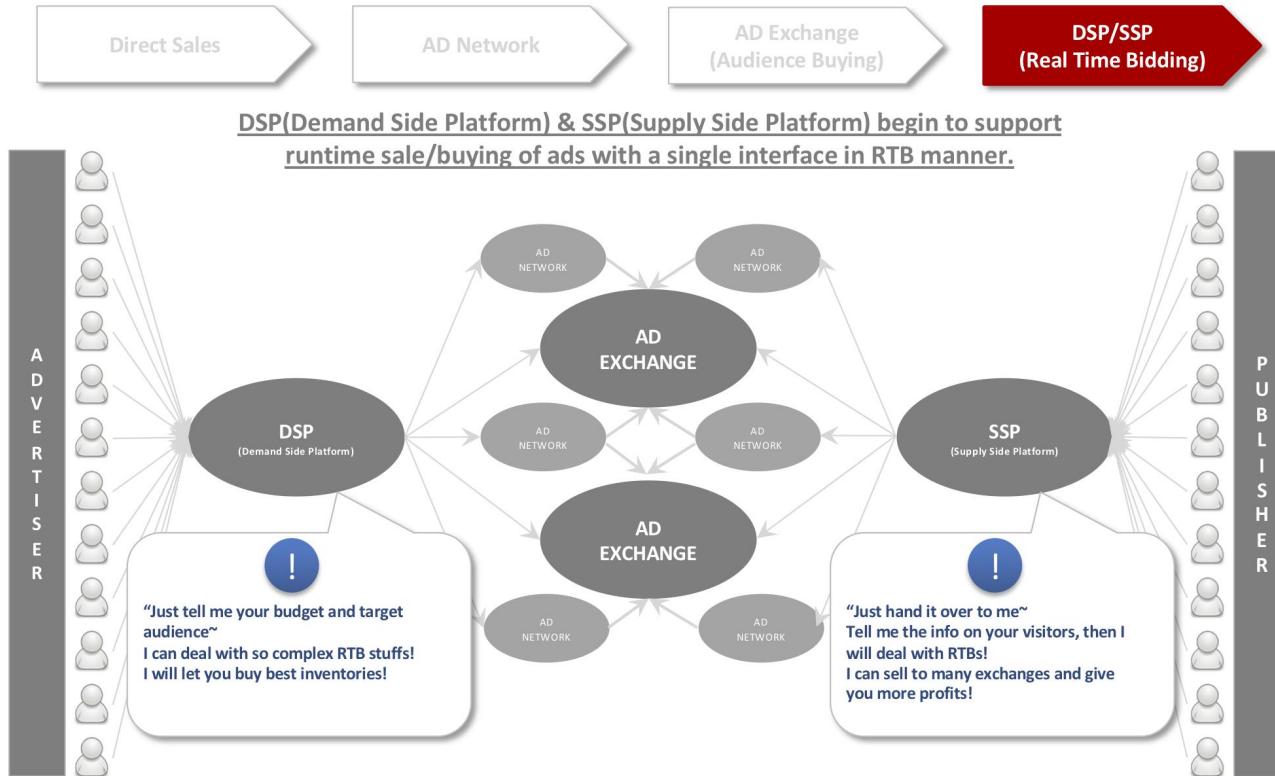
# Evolution of digital ad platform: ad exchange (2/3)



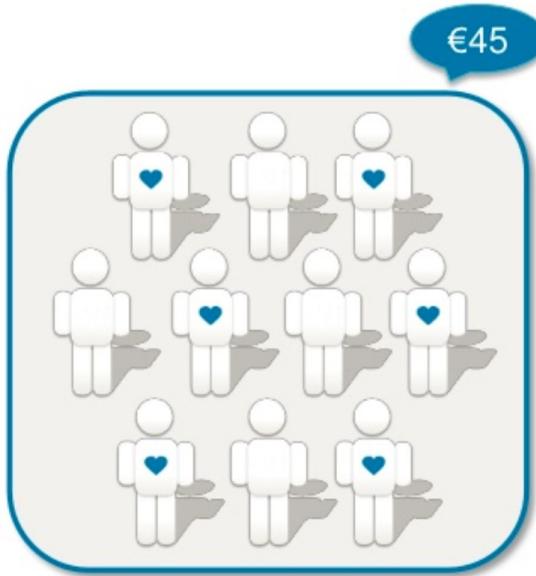
# Evolution of digital ad platform: ad exchange (3/3)



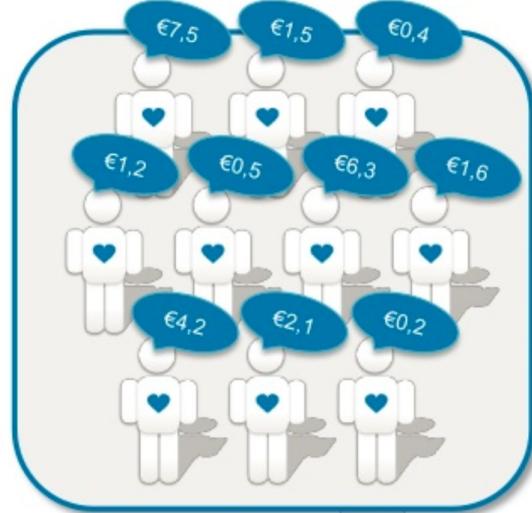
# Evolution of digital ad platform: DSP and SSP



# Why Real-Time Bidding: Granularity Matters

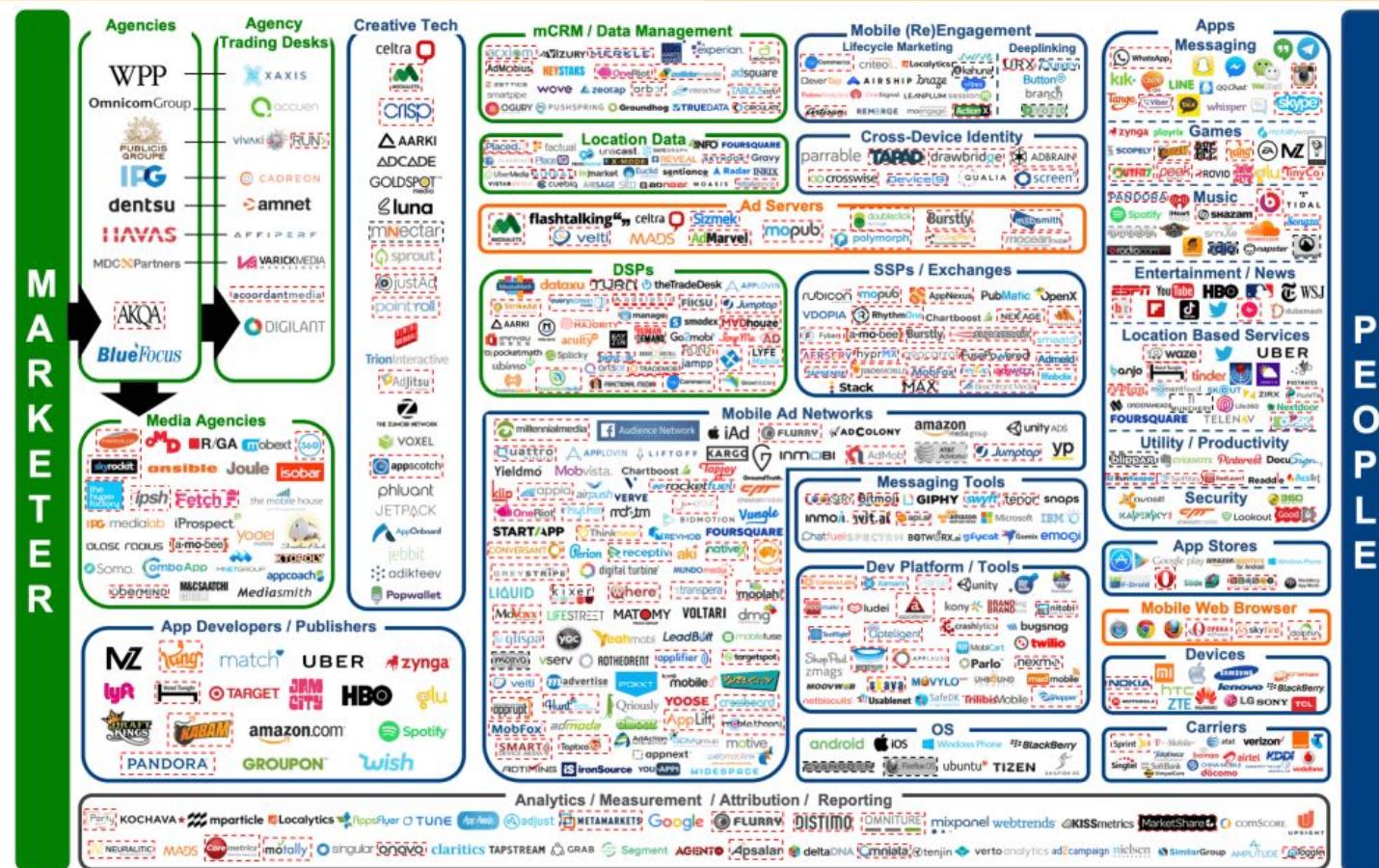


Non-RTB:  
Impressions  
purchased in bulk



Real-time Bidding:  
Each impression won has  
unique purchase value

# MOBILE LUMAescape



# A few things about Moloco

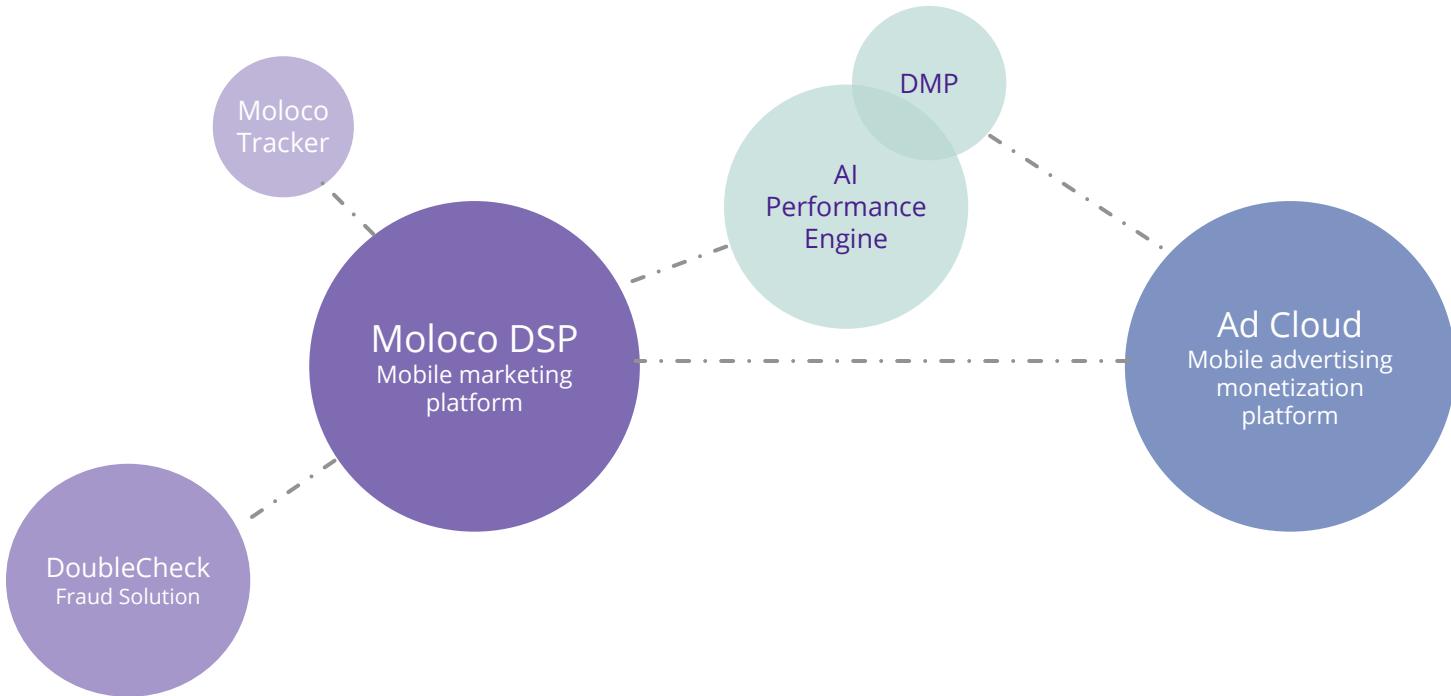


# Moloco Offices

Started in Palo Alto and working from 8 remote offices



# Moloco Products



# Moloco performance recognition

AppsFlyer Performance Index Power-ranking Top 10 & Kochava Traffic Index APAC & North America #1



Evaluation based on install volume,  
user quality and user in-app performance



Ranking based on signal clarity,  
fraud rate and user quality

\* AppsFlyer Index: <https://www.appsflyer.com/2018indexpage/>

\* Kochava Index: <https://lnkd.in/gmVHF0m>

# Moloco leadership



**Ikjin Ahn**  
**CEO, Co-founder**  
Google Android Big data  
Tech Lead Manager



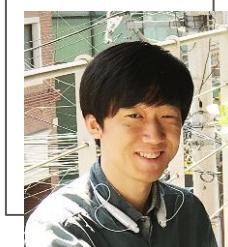
**Sehyuk Park**  
**Co-founder**  
Oracle Software  
Engineer



**Brian Yoo**  
**COO**  
Google Analyst



**Donghwan Jeon** CTO  
Google Cloud Platform  
Senior Software  
Engineer



**Hyeonseo Ku**  
**APAC Director**  
Amazon Payment  
Software Dev  
Engineer

# Moloco people are from...



Microsoft



삼성전자



ORACLE®

facebook.



Goldman  
Sachs



McKinsey&Company

TBWA\

NAVER



SK telecom

Cheil

# Education background of Moloco people

Ph.D.

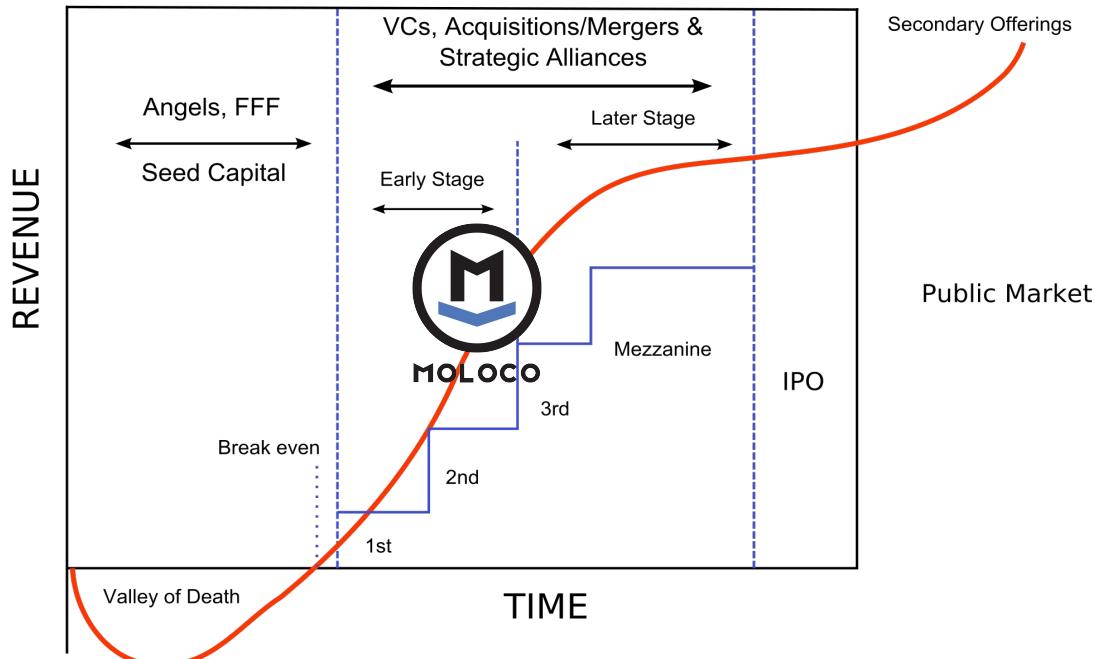
16

M.S. (incl. MBA)

23

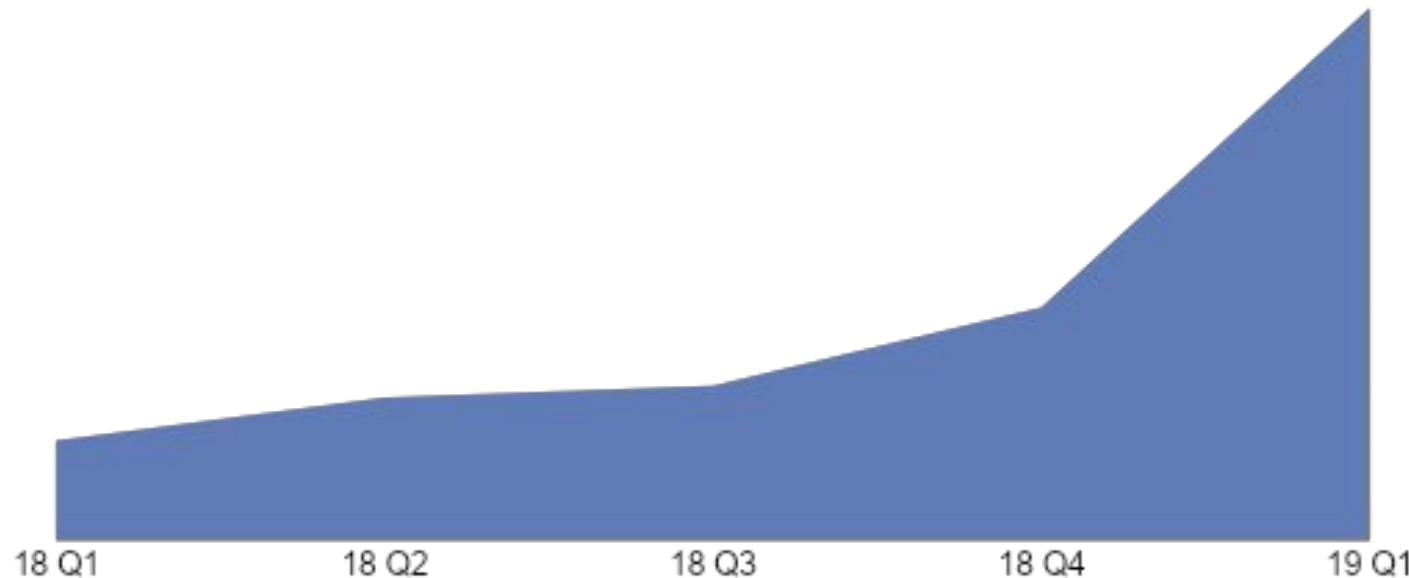
# Growth of Moloco

## Startup Financing Cycle

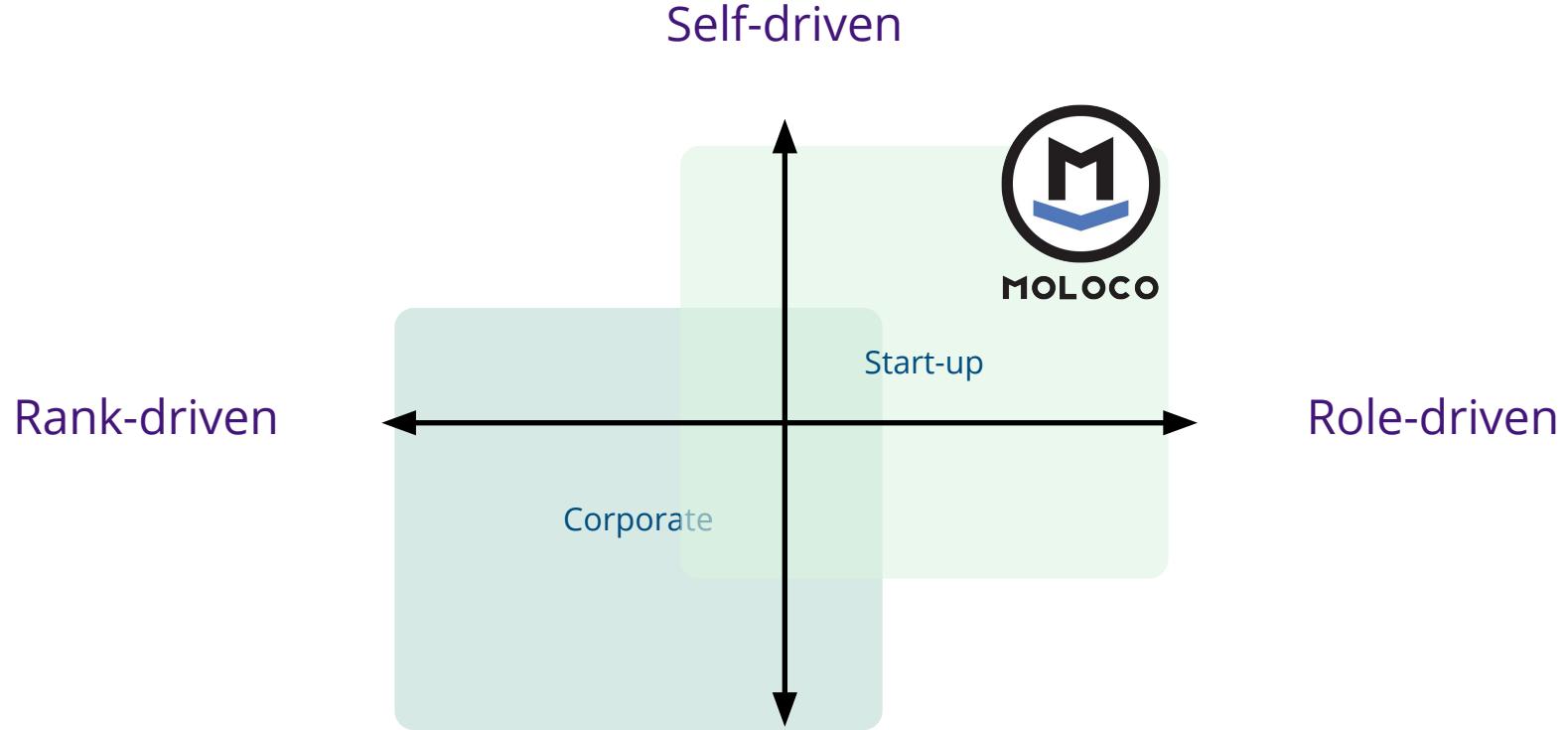


# Growth of Moloco

Quarterly revenue of Moloco



# Working style in Moloco



# How Moloco people work



Google Calendar



Sun	Mon	Tue	Wed	Thu	Fri	Sat
21 Moving	22 부재중 Chai 000 Ethan 000	23	24 diko 000 diko@Tokyo Myunggeun 000 haden 000 Simon WFH Will in @Moloco : milli's study book	25	26 Nidhi @Bangkok Chai @Bangkok	27



## Moloco people are...

Autonomous

Excellent in problem finding and solving

Obsessive in quality

Hard working

# Life at Moloco



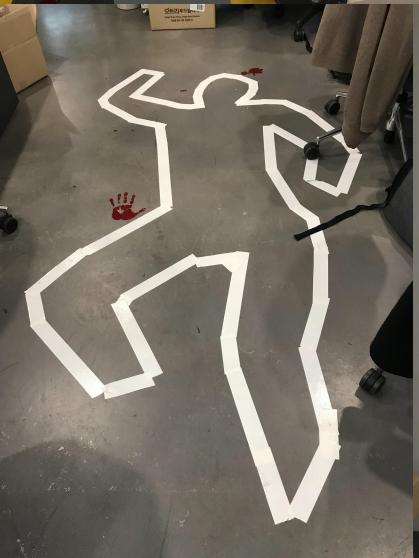
“Moloco 최고의 복지는  
가로수길”

# 2019 Hawaii Global Offsite

Moloco Event



# Halloween 2019



## If you want to know more about Moloco...

- <https://web.facebook.com/molocoinc/>
- <https://web.facebook.com/Molocokorea/>
- <https://medium.com/@moloco>
- <https://medium.com/@molocokr>
- <https://www.linkedin.com/company/moloco/>
- <https://www.linkedin.com/company/moloco/jobs/>

# How Moloco works as a DSP



# **ML models by Moloco**

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# The problem a demand-side platform (DSP) encounters

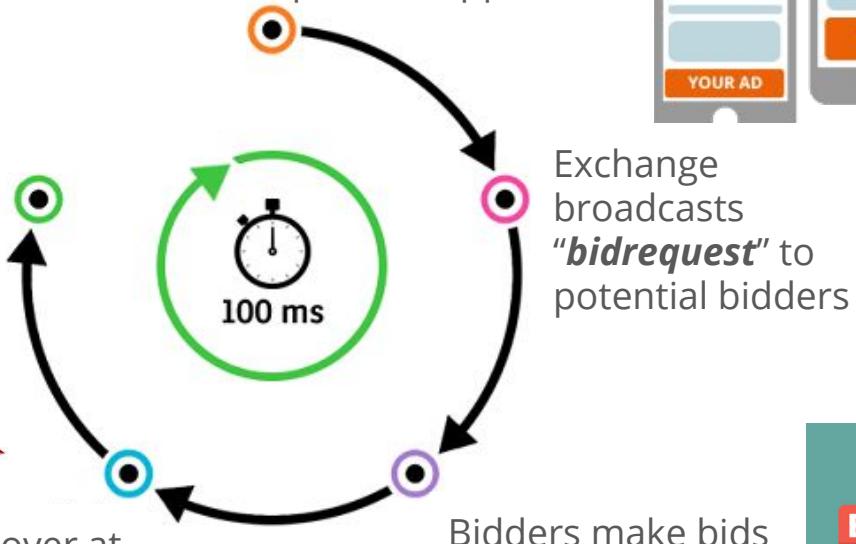


Winning ad  
is served  
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Auction is over at  
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*bidrequest* is generated  
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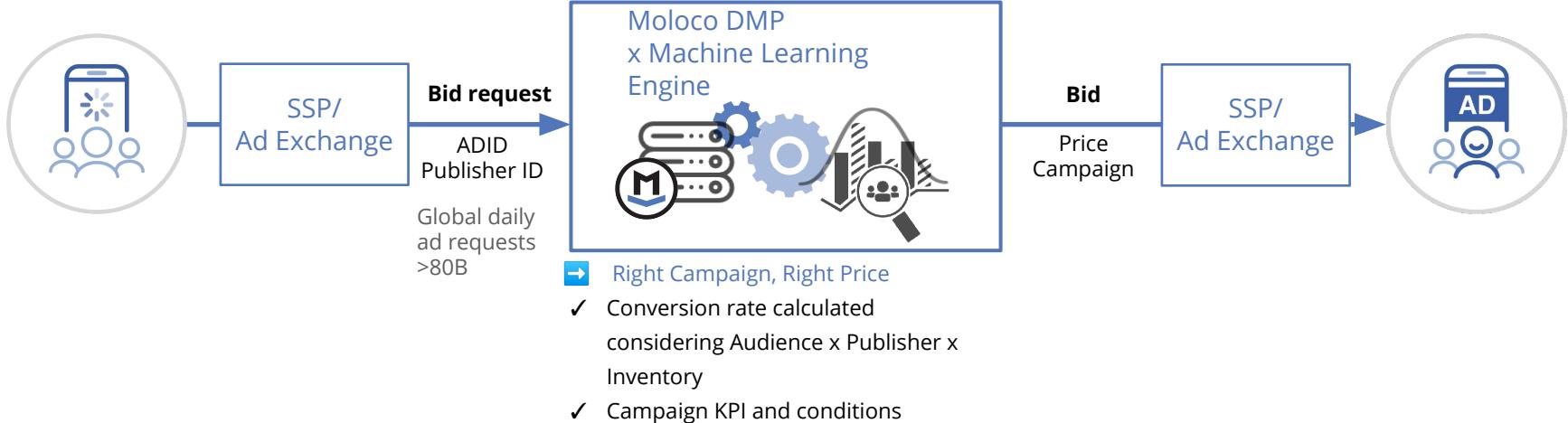


DSP determines the  
bid price on behalf of  
advertisers



# How Moloco handle this problem with ML models

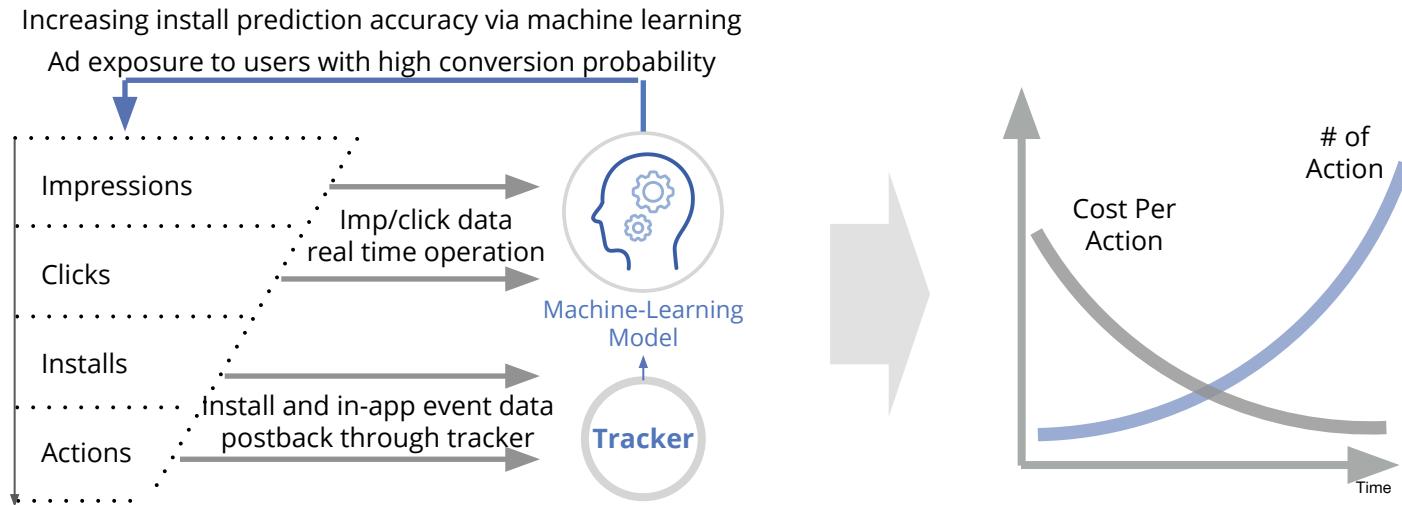
100% Programmatic & Transparent



ML engine predicts the user conversion rate after considering factors like user data/publisher/inventory/creatives format  
Appropriate price for each ad impression shown

No reselling or re-brokering with Affiliates, only reliable and high quality 100% RTB inventories are secured

# Improving performance by machine-learning model



Optimization with the help of real time postbacks regarding Imp, click, install, in-app actions etc.  
Boost the performance by increasing the accuracy of install/action prediction models  
(More the data accumulated, easier and faster it is to do the optimization)

## Data: sample bid request (1/2)

```
"app": {  
    "bundle": "com.fivemobile.thescore",  
    "cat": ["IAB12", "IAB17", "news", "sports"],  
    "id": "agltb3B1Yi1pbmNyDAsSA0FwcBiq-uwTDA",  
    "name": "TheScore - Android App",  
    "publisher": {  
        "id": "agltb3B1Yi1pbmNyEAsSB0FjY291bnQYpPHvEww",  
        "name": "The Score"  
    },  
    "ver": "6.0.1"  
},
```



## Publisher App Info

```
"imp": [{  
    "banner": {  
        "api": [3, 5],  
        "battr": [1, 3, 8, 9, 10, 13, 14, 6],  
        "btype": [4],  
        "h": 50,  
        "pos": 1,  
        "w": 320  
    },  
    "bidfloor": 0.970,  
    "displaymanager": "mopub",  
    "displaymanagerver": "4.14.0",  
    "ext": {  
        "adid": "12345678901234567890123456789012",  
        "advertiser": "12345678901234567890123456789012",  
        "app_id": "12345678901234567890123456789012",  
        "carrier": "12345678901234567890123456789012",  
        "device": "12345678901234567890123456789012",  
        "geo": "12345678901234567890123456789012",  
        "ip": "123.45.67.89",  
        "os": "12345678901234567890123456789012",  
        "ua": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/58.0.3029.110 Safari/537.36",  
        "vid": "12345678901234567890123456789012"  
    },  
    "id": "12345678901234567890123456789012",  
    "impid": "12345678901234567890123456789012",  
    "lmt": false,  
    "nms": "12345678901234567890123456789012",  
    "oos": true,  
    "pmp": false,  
    "pmpid": null,  
    "rtbids": [{"id": "12345678901234567890123456789012", "pmp": false, "pmpid": null, "vastxml": "

ad content

", "vastxmltype": "text/html"}]  
},  
{"id": "12345678901234567890123456789013", "impid": "12345678901234567890123456789013", "lmt": false, "nms": "12345678901234567890123456789013", "oos": true, "pmp": false, "pmpid": null, "rtbids": [{"id": "12345678901234567890123456789013", "pmp": false, "pmpid": null, "vastxml": "

ad content

", "vastxmltype": "text/html"}]}]
```

## Ad Slot Info

# Data: sample bid request (2/2)

```
"device": {  
    "geo": {  
        "city": "Fontana",  
        "country": "USA",  
        "lat": 34.039214,  
        "lon": -117.46634,  
        "region": "CA",  
        "zip": "92335"  
    },  
    "ifa": "099c14f1-f3c5-4da2-87b1-XXXXXXXXXX",  
    "ip": "99.23.172.121",  
    "language": "en",  
    "make": "LGE",  
    "model": "LGMS330",  
},  
    "user": {  
        "keywords": "allowHouseAds:false,language:en,GPS:true,league:nfl,  
        tab:news,page:article,country:US,  
        region:California,city:Fontana,accountType:email,  
        articleID:1390672,playerID:/football/players/41055,  
        teamID:/football/teams/32,/baseball/teams/26,/football/teams/27,  
        /football/teams/676,/basketball/teams/18,  
        dmp_LbkziWS8,dmp_LYS180qJ,dmp_LYS1nWJ2,dmp_LV5R4X2g"  
    }  
}
```

ADID, IDFA

Your Device Info

What App Knows about You.  
(Please bid higher with confidence!)

# Data: sample bid response

```
"id": "1234567890", "bidid": "abc1123", "cur": "USD",
"seatbid": [
  {
    "seat": "512",
    "bid": [
      {
        "id": "1", "impid": "102", "price": 9.43,
        "nurl": "http://adserver.com/winnotice?impid=102",
        "iurl": "http://adserver.com/pathtosampleimage",
        "adomain": [ "advertiserdomain.com" ],
        "cid": "campaign111",
        "crid": "creative112",
        "attr": [ 1, 2, 3, 4, 5, 6, 7, 12 ]
      }
    ]
  }
]
```

bidding price (CostPerMillis) :  
That is, **\$0.00943**

campaign, creative choice

Find the optimal!  
In real time, fast enough.

- (1) How to make it happen?
- (2) How to compute the price  
(i.e., what's the bidding strategy)?

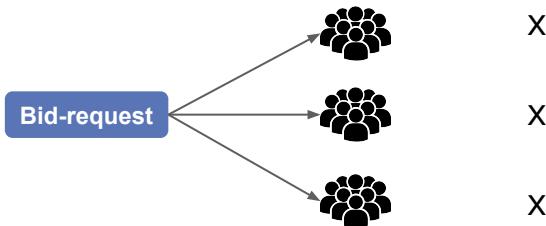
# What pricing strategy a DSP can have?

Simple pricing strategy which requires low tech (and high manual configurations)

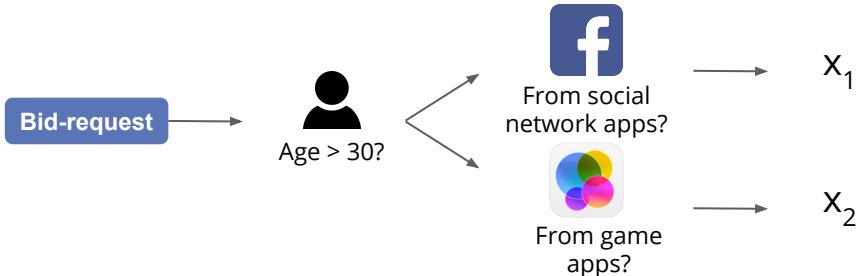
## 1. Flat pricing



## 2. Segment-based pricing



## 3. Rule-based pricing



# How do we estimate the value of an impression?

Suppose we run an app-install campaign with payout of  $\$r$  for each install

Let  $Q$  be the probability that a certain user installs the campaign app after an ad impression, i.e.,  $P(\text{conversion} \mid \text{impression})$

- If the user installs, we receive  $\$r$
- If the user does not install, we earn nothing
- Expected return =  $\$r * Q + \$0 * (1 - Q)$

Value price = reward of target action \* target action probability

Thus, we need to build an ML model to predict  $Q$ .

# Is it Optimal to Bid at Value CPM?

- In 2nd price auction, the **highest bidder wins**, and pays the **second highest bid price**
- Let  $p_w$  be the distribution of other bidders' highest bid
- Expected profit of bidding at  $p$  is
  - $E[ (r \mathbb{1}\{\text{install}\} - p_w) \mathbb{1}\{p_w \leq p\} ]$
  - $= \int_0^p (r Q - x) d\text{Prob}(p_w \leq x)$
  - $= \int_0^p (r Q - x) P(p_w = x) dx$
- For any distribution of  $p_{w'}$  the expected profit
  - Increases in  $p$  for  $p \leq r Q$
  - Decreases in  $p$  for  $p > r Q$
  - Bidding at  $r * Q$  (value CPM) is optimal

# How to compute the price?

- (Well-known case) Finding bid-price for a certain ad with following assumption.
  1. the client pays us  $\$r$  for one click.
  2. the second price auction.
  3. we know the probability  $p$  for the device to make a click from our ad.
  4. Market Price (i.e. highest bid-price from others) distribution  $M$  is known (with p.d.f  $f_M$ ).
- Then easily the expectation of revenue and profit for bid-price  $b$  is:

$$\mathbb{E}[\text{revenue}](b) = P(M < b)pr$$

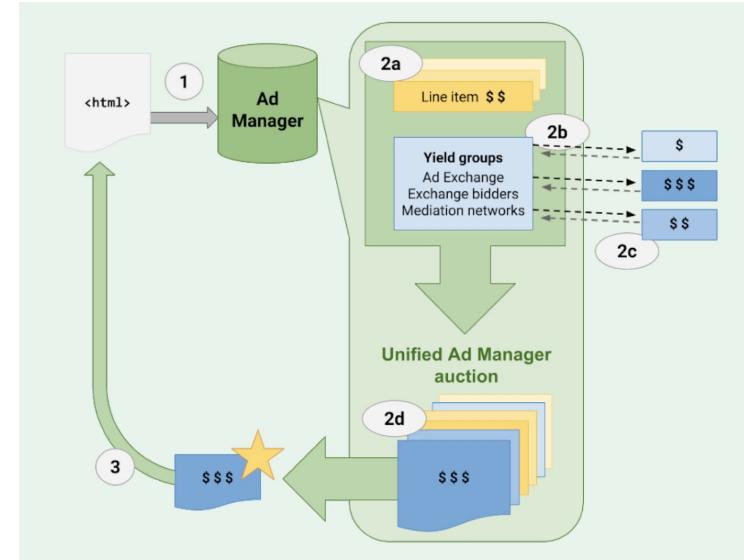
$$\mathbb{E}[\text{profit}](b) = P(M < b)pr - P(M < b)\mathbb{E}[M|M < b] = \int_0^b (pr - u)f_M(u)du$$

- If there is no restriction of revenue, profit-maximizing bid-price is  
And this is independent of  $M$ . Generally not this easy!

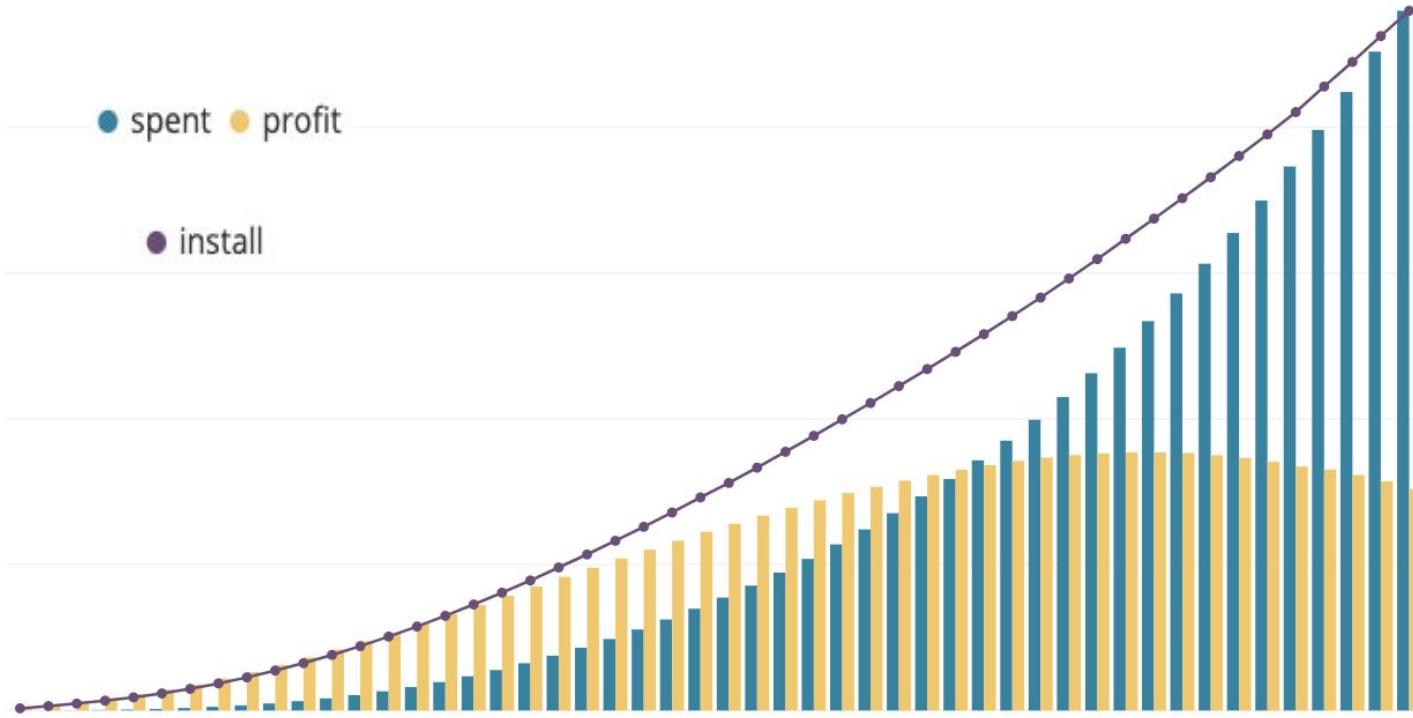
$$b = pr$$

# In Practice...

- No exchanges run pure a 2nd-price auction
  - Dynamic floor price (ADX)
  - Multiple bid requests with different floor prices (MOPUB)
  - First-price auction (SAMSUNG)
  - Header bidding & mediation
- Ad-serving cost was NOT considered in the previous analysis
- Control *multipliers* to achieve certain eCPI or volume



# How to compute the price? - Realization



# Moloco models by campaign status

Lookalike	Install Optimization ML	Action Boosting	Action Optimization DNN
			
Seed ADID/ all postback	Moloco-driven Install events	All postback + Moloco data	Moloco-driven action events

As we gather event data (like impressions, click, install, actions, etc) through campaign, ML optimizes the campaign and with enough data, newly matured advance ML model is applied in order to accomplish the campaign goal

# Initiating lookalike models



All postback  
or Seed ADID

Lookalike Model +  
Install Optimization

Performance  
Boosting

Best results with the help of healthy seed ADIDs/ all postback settings  
Boosting the early stage performance and shorten the period for stabilization via look-a-like model

# Logistic Regression (LR) Model

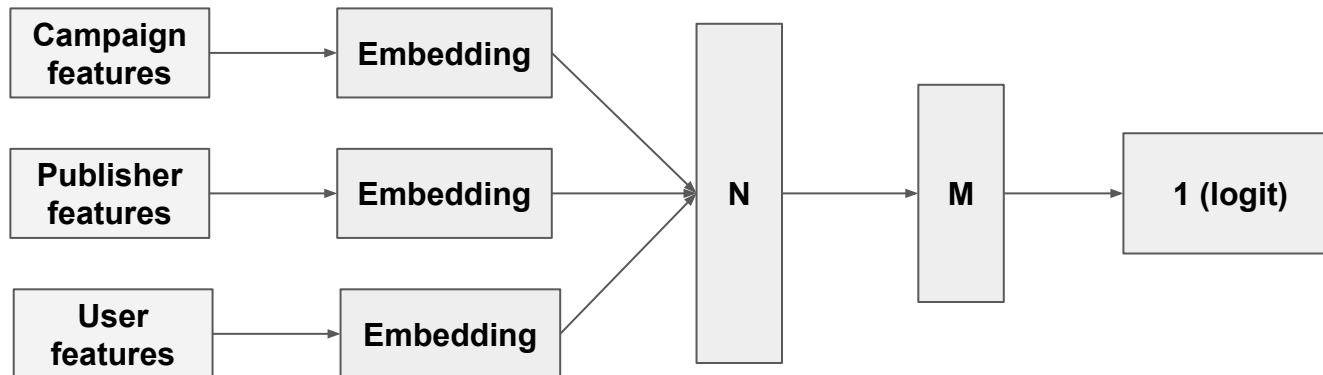
- Logistic regression after getting weighted sum of features and log(feature) values
- Performs relatively well with a small set of data
- Inefficient in exploring new publishers
- Feature engineering is important.
  - Features on publisher, user, campaign
  - Interaction terms, e.g.,
    - publisher X campaign
- *Memorization*, rather than *generalization*
- Can be served in a very fast manner

Campaign		Age		Publisher	
Cmpgn#1	0.4	< 20	0.3	APP#1	0.3
Cmpgn#2	0.1	>= 20	-0.1	APP#2	-0.4
				APP#3	0.2

Pub × Campaign	
APP#3 Cmpgn#1	0.2
APP#1 Cmpgn#2	0.3

# Deep neural network (DNN) model

- Reducing repeated computation of matrix is a key.
- Variations of LR/DNN models
  - # of hidden layer, # of hidden unit, layer architecture
  - Selection of positive events: click, install, purchase, etc.



# **Infrastructure by Moloco**

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# Challenges in building scalable ad system

## **Small latency with high volume of network traffic**

- Real-time bidding (RTB) exchanges require us to respond within 100ms
- We handle >1.6M bid requests per second at peak (>80B per day)

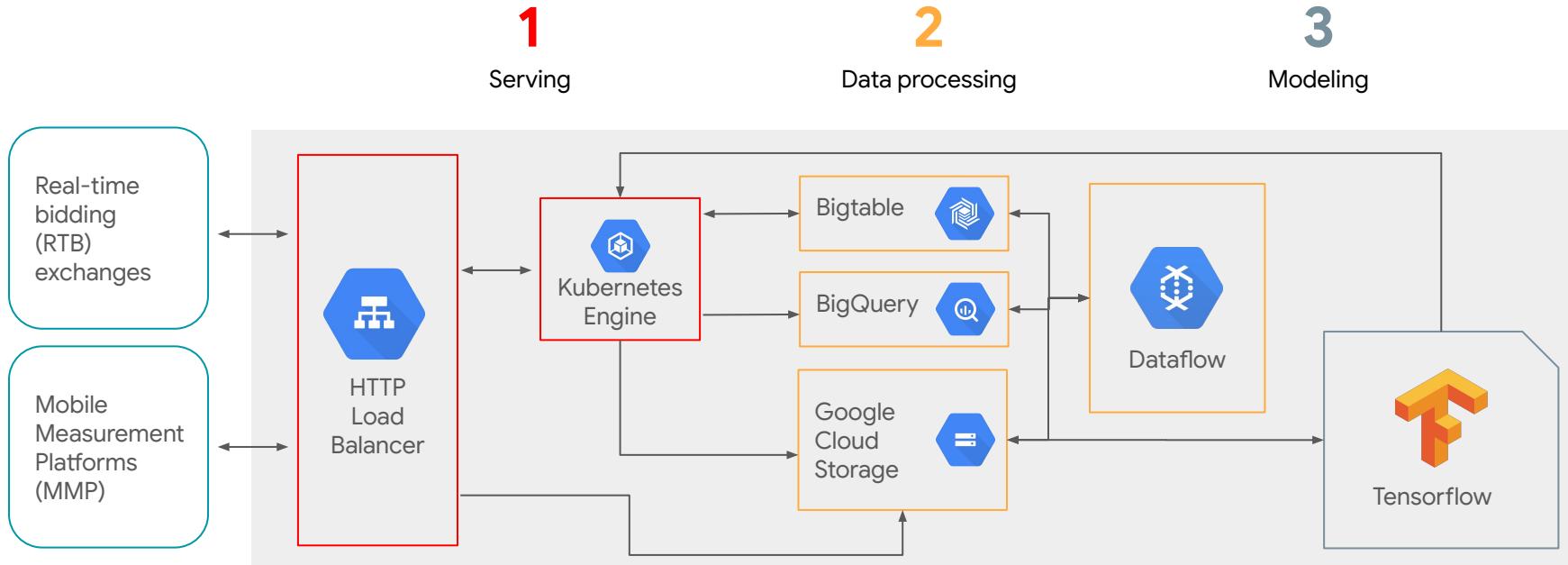
## **Transforming big data into machine learning models**

- >165 TB of new data is generated daily, and we use the accumulated data for training our ML models

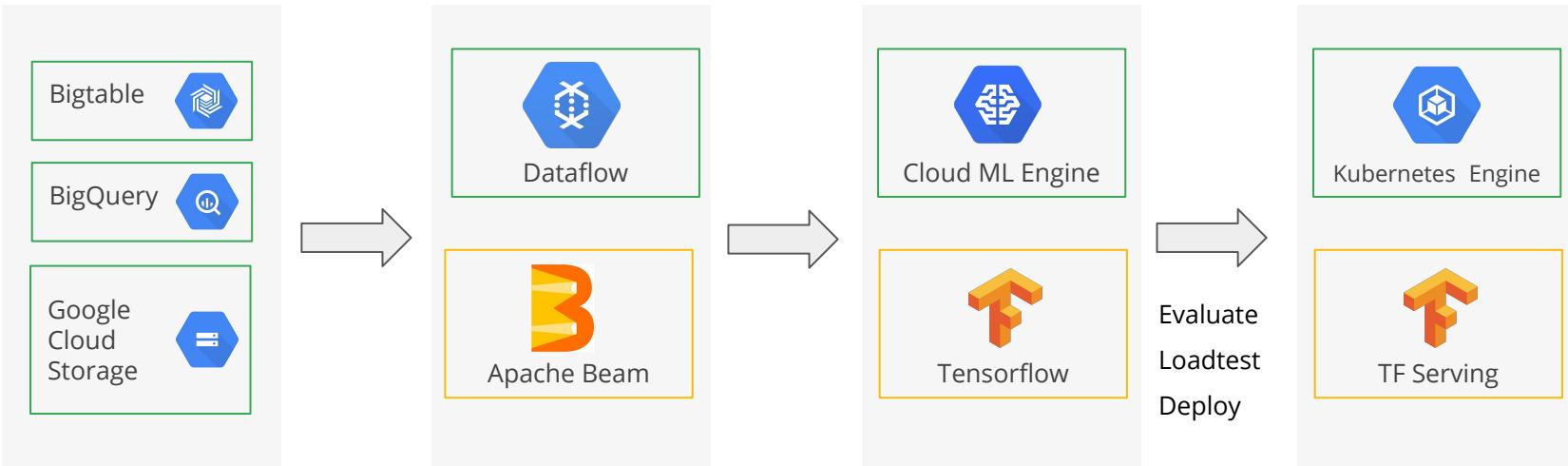
## **Collaborative tools for complex analysis around big data**

- Our data scientists & modelers need collaborative tools to analyze large, complex data

# How Moloco is using GCP



# Modeling Pipeline



Data

- 5B training examples per week
- 400+ instances

Produce training data as TF examples via python Dataflow

Train Tensorflow model with Cloud ML Engine

- 52 high-CPU instances
- Distributed training

Serve traffic via TF Serving on Compute Engine

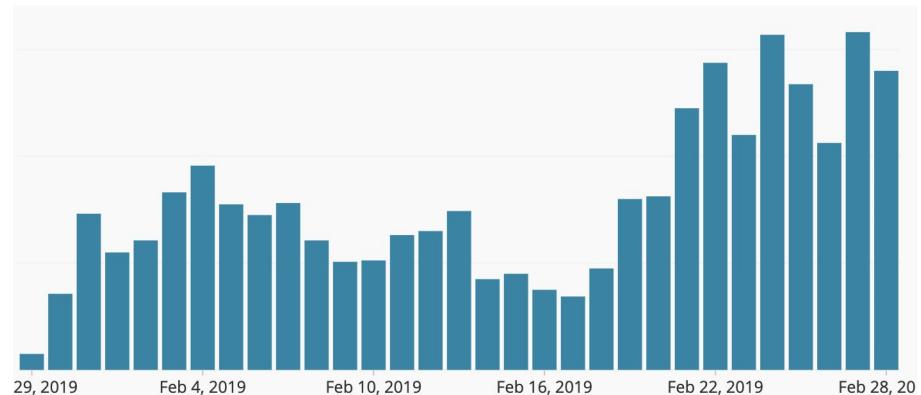
- 300+ high-memory instances
- 100+ candidates scored per inference
- 400k+ peak QPS with median latency < 10ms

# Example: user acquisition campaign

Daily CPI (Cost per Install)



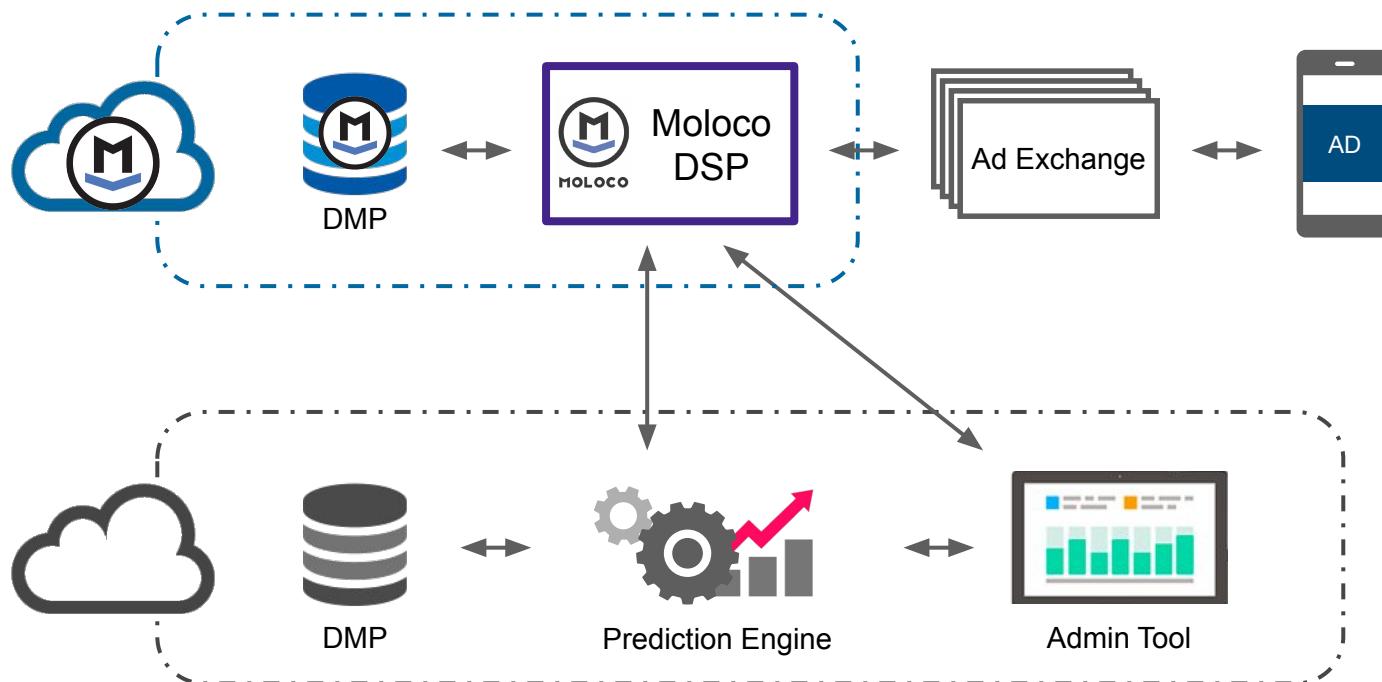
Daily Install



# Moloco Ad Cloud

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# Moloco Ad Cloud enables clients to build custom models using their first-party data





**MOLOCO**

Any Questions...?