Can Machines Learn Beauty?

DataTalks 2019

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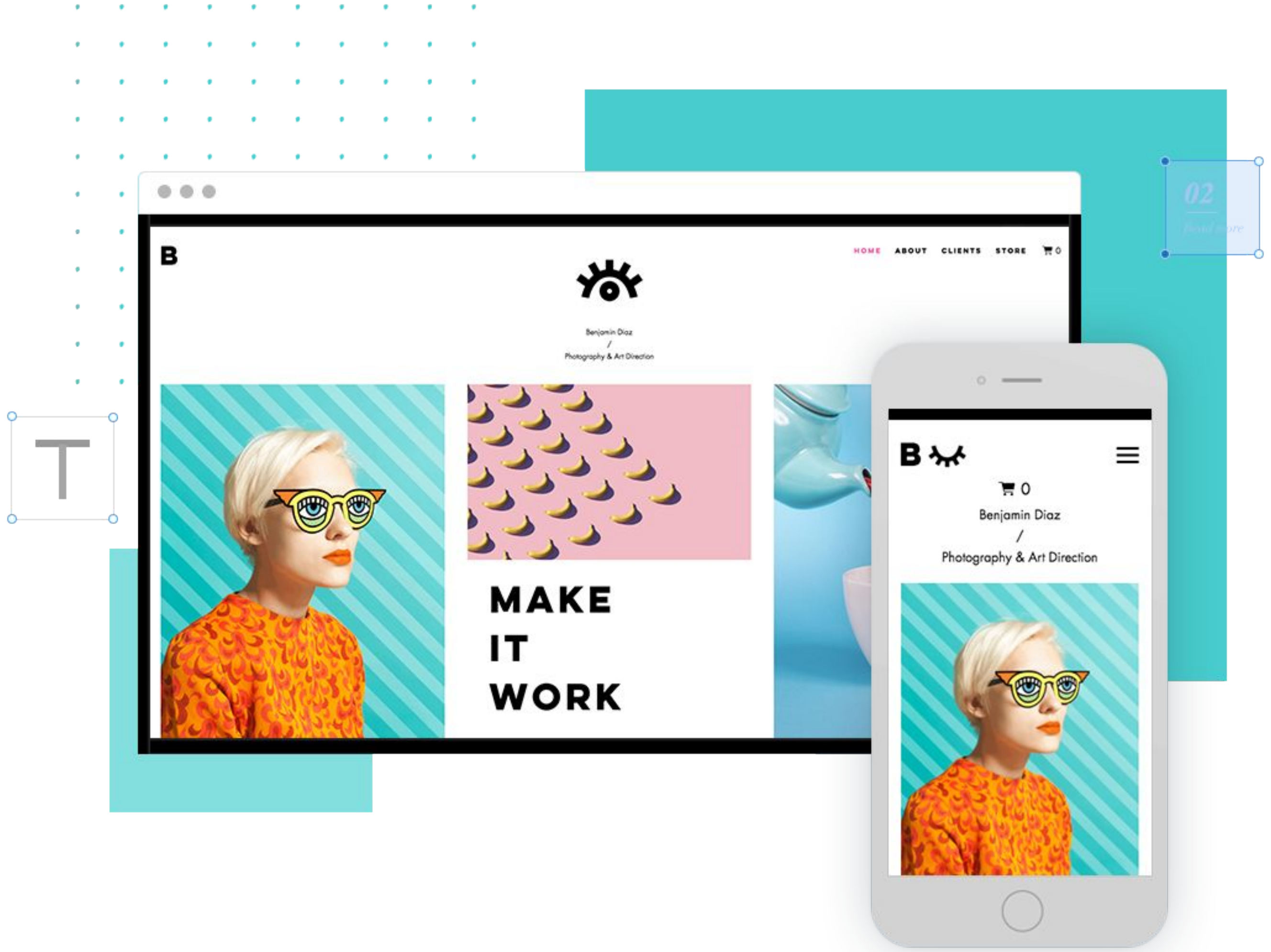

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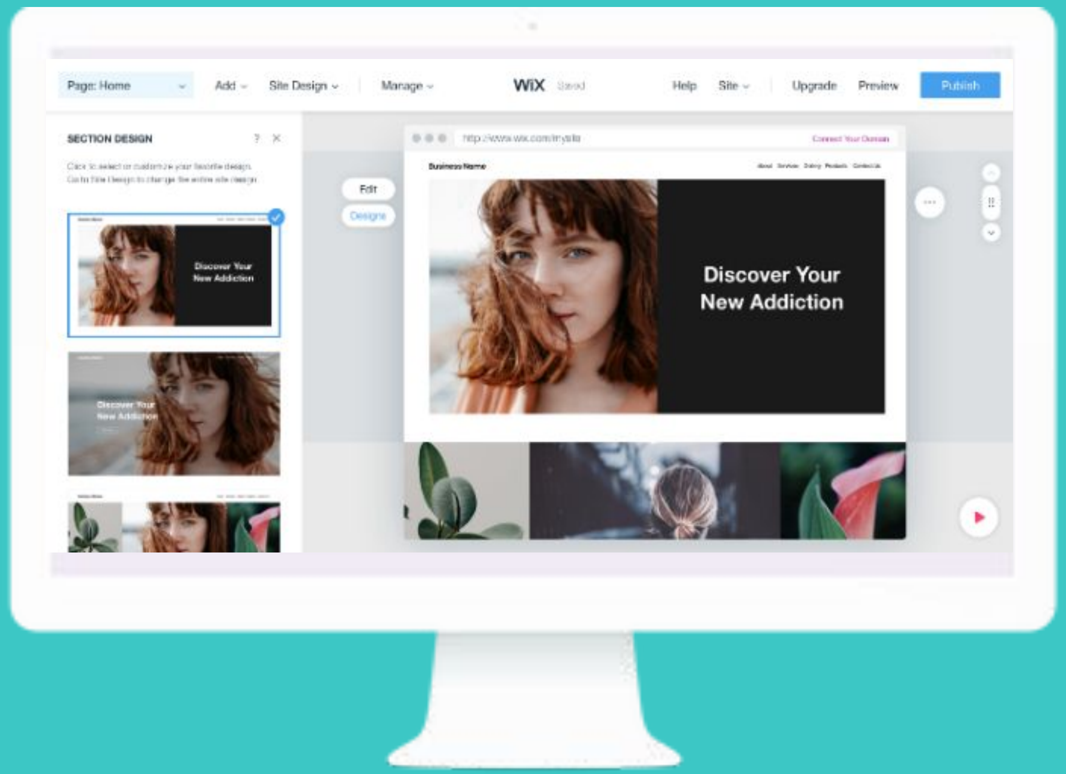
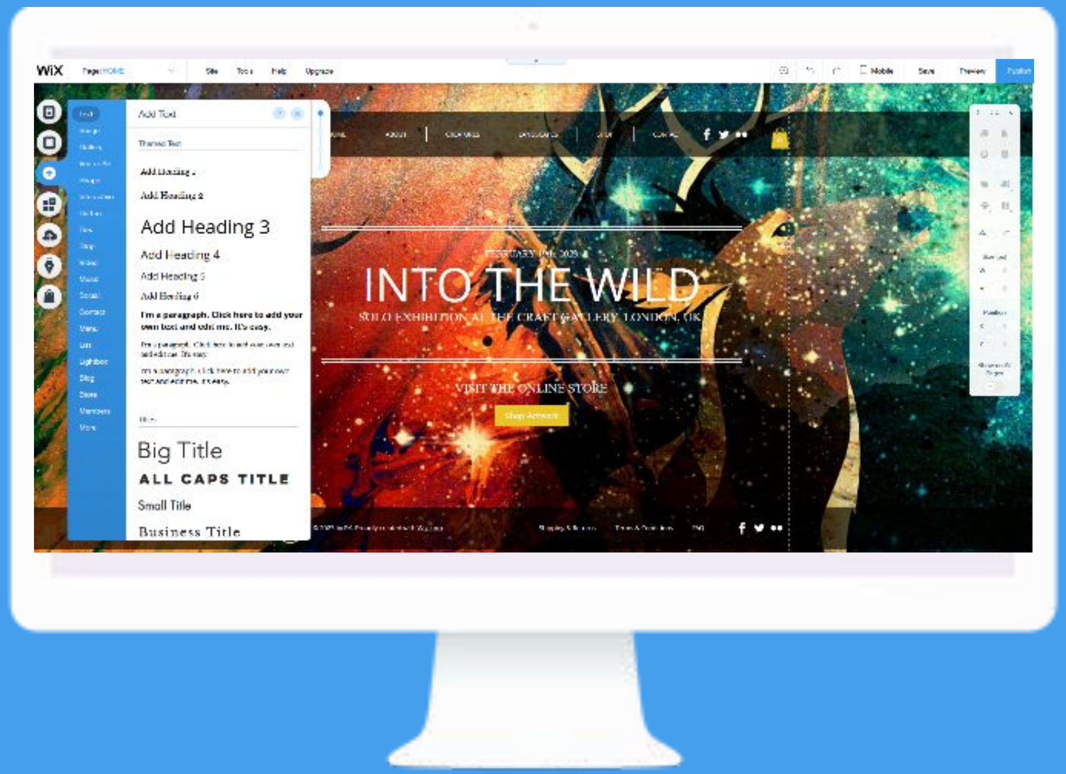
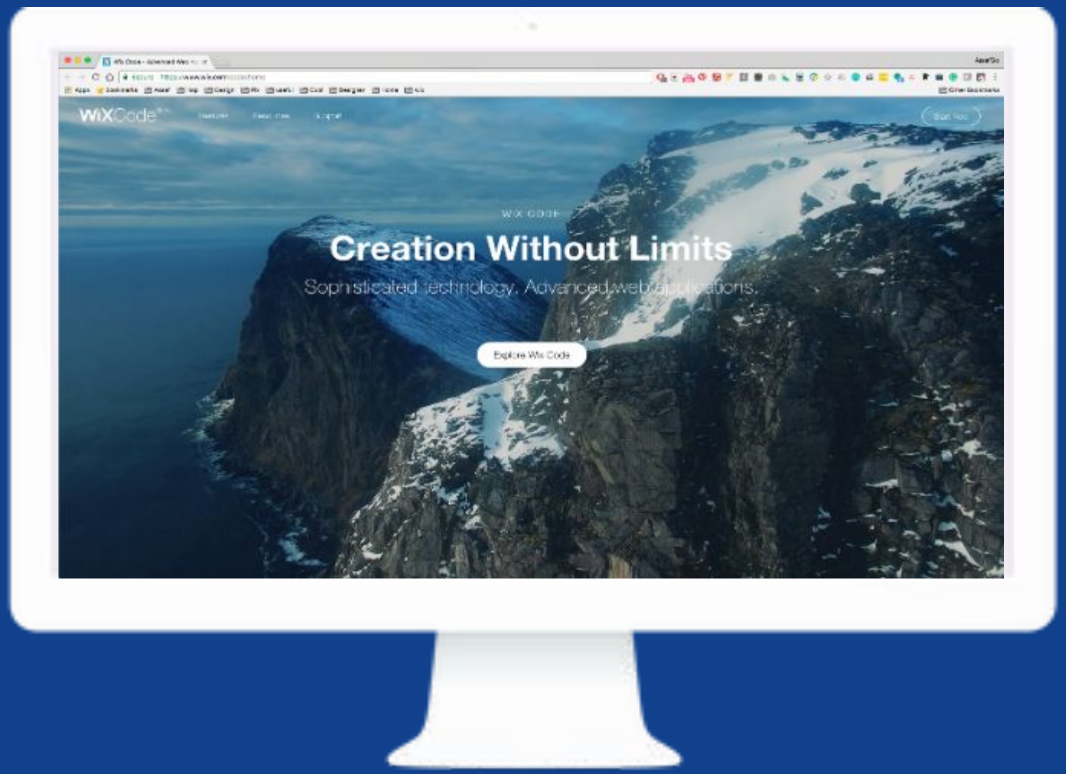


Wix Editor



Corvid



Novice

Expert

154M

Registered Users

4.3M

Paying Customers

IT'S
THAT
EASY

START
STUNNING

IT'S
THAT
EASY

START
STUNNING

BUSINESS GOALS

Data Science

DATA CURATION

DATA SCIENTISTS

ENGINEERING

We work with

LOTS OF DATA

Images

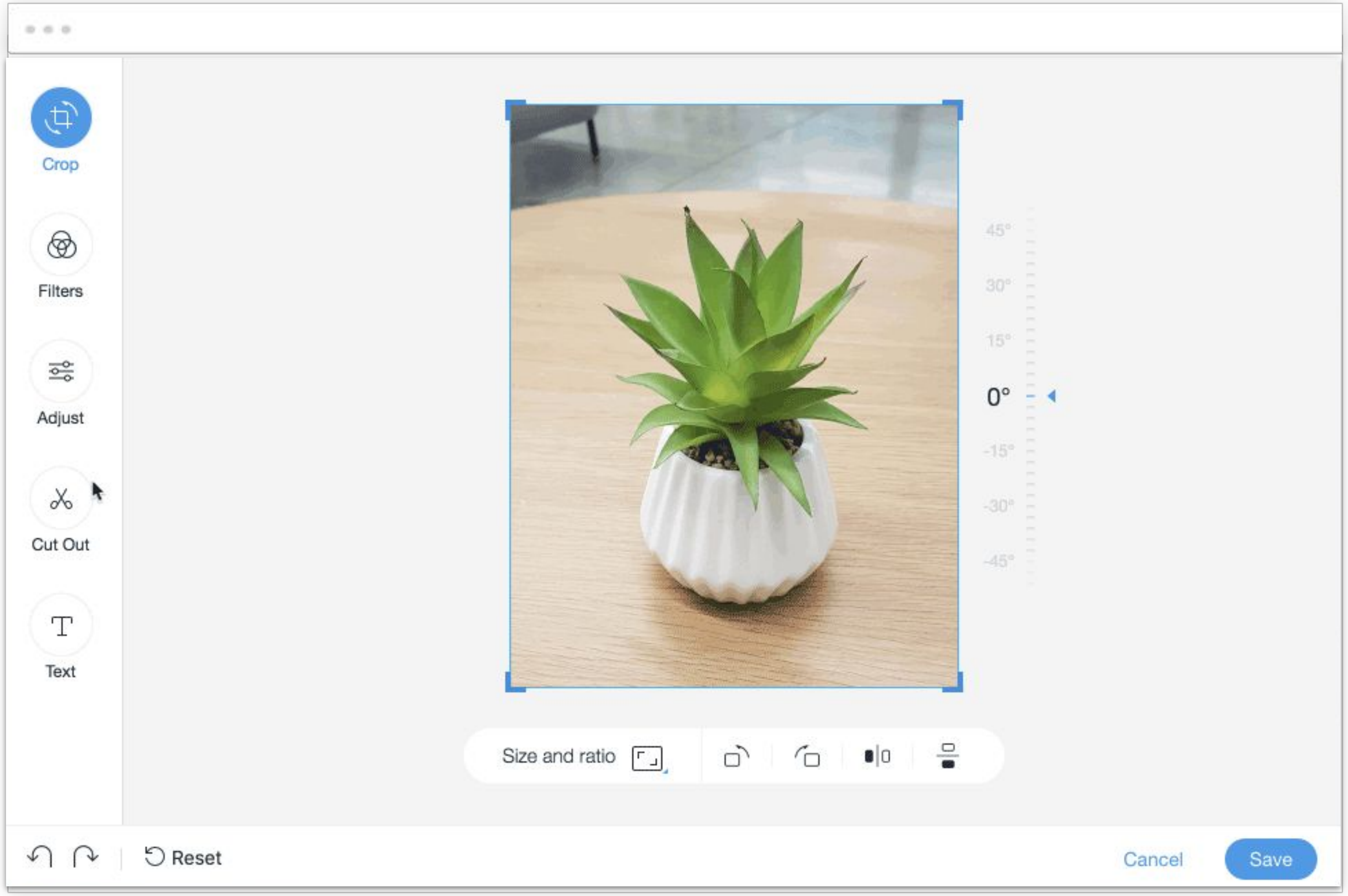
Website Structure

Financial

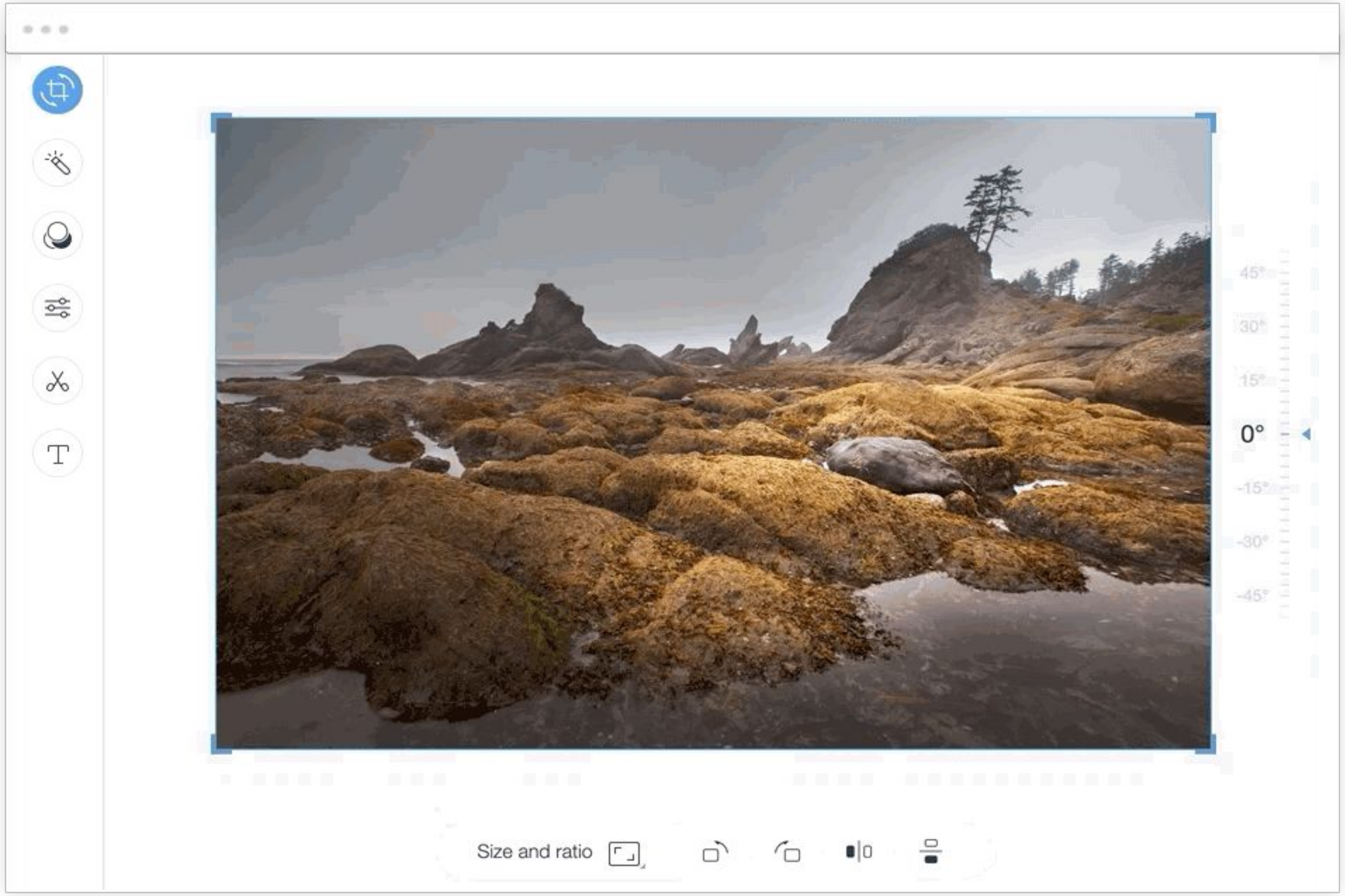
Text

User Actions

Object Cutout

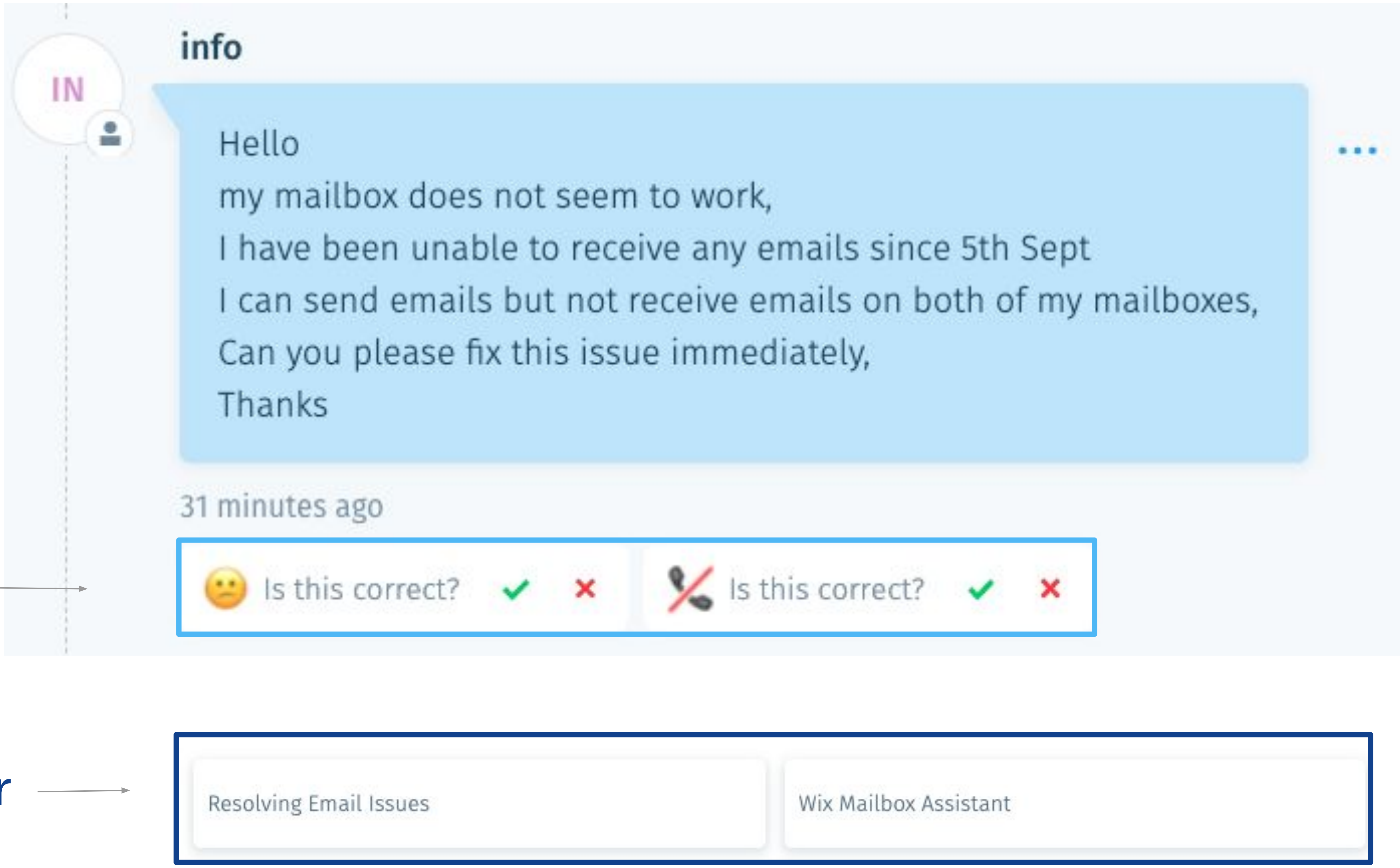


Auto Enhance



Revenue Forecasting

Support ticket analysis

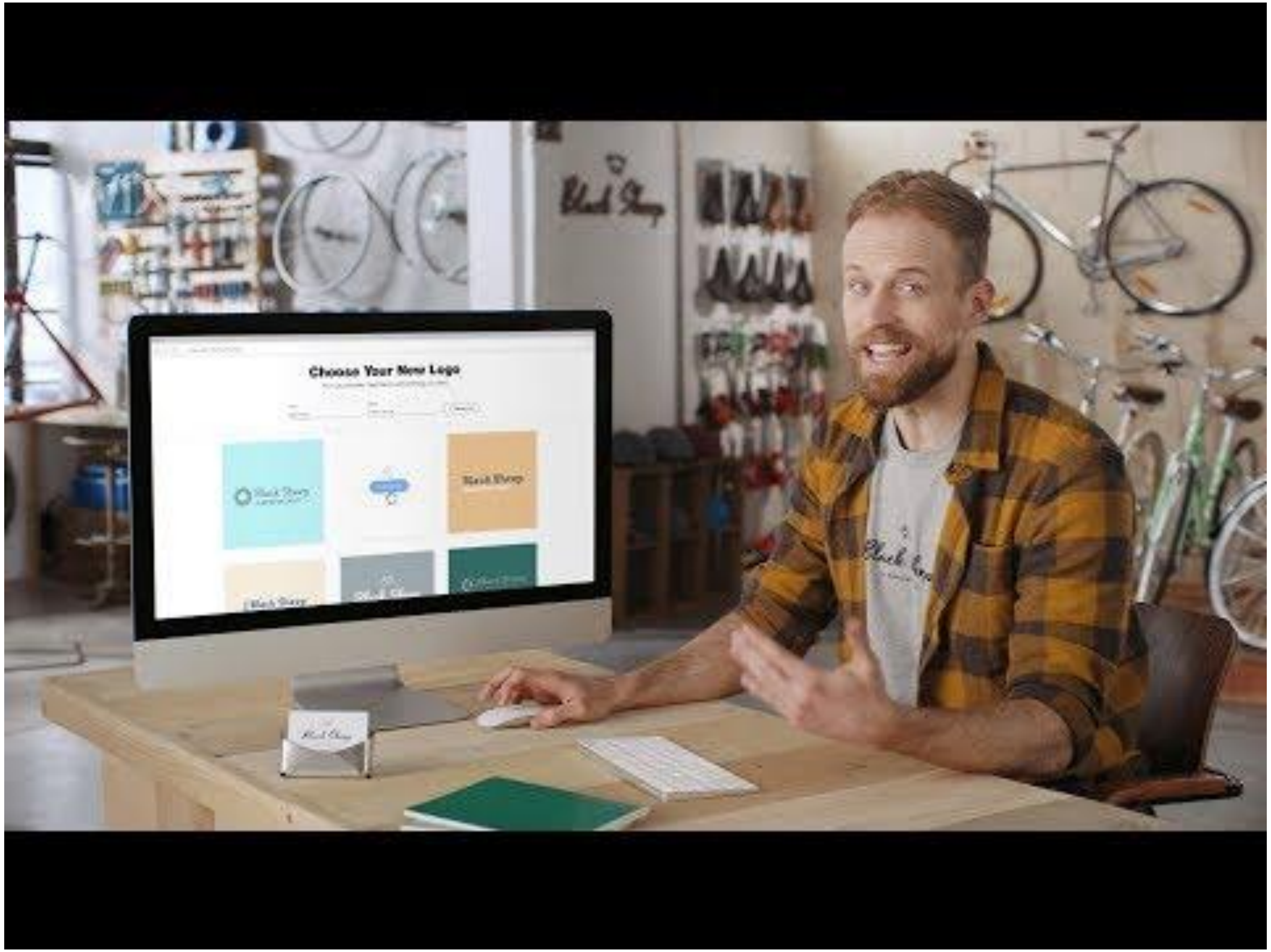


Sentiment Analysis

Article Recommender

And many many more...

Teaching Machine Beauty



https://www.youtube.com/watch?v=YAgVF_6NnEI

THE GOAL :

Help Users Create More Beautiful Logos

THE GOAL :

Help Users Create More **Beautiful** Logos

Let's build a model which understands Beauty...

Data Labeling

INPUTS

Yoga4U
Yoga and Pilates Studio

Southern Grace Candle and Design

XYZ Solutions Ltd.
Technology Mentoring

Light fruit
Hagamos el cambio

Nanaimo Pet Services
The Best For Your Best Friend

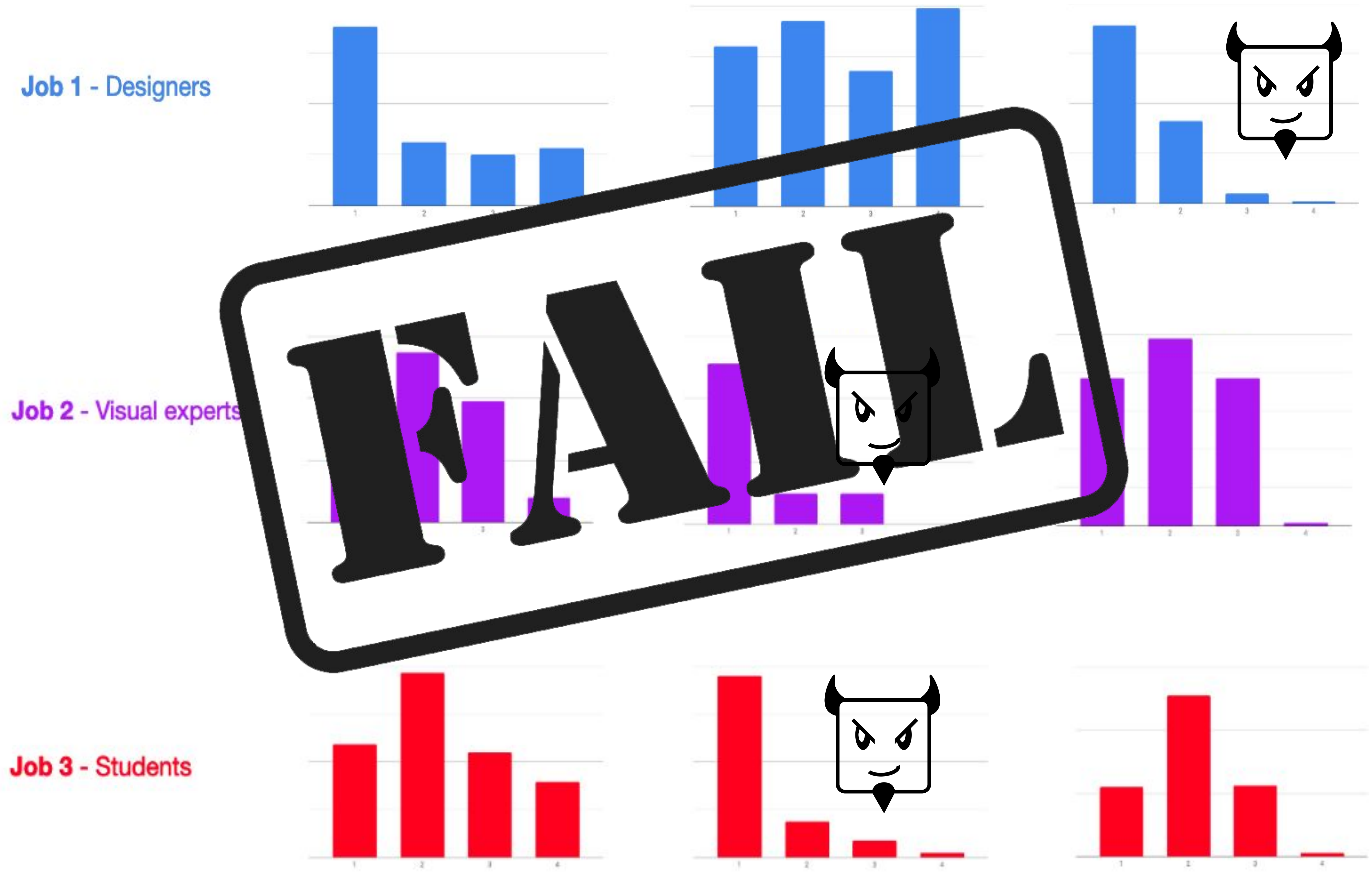
LABEL

?

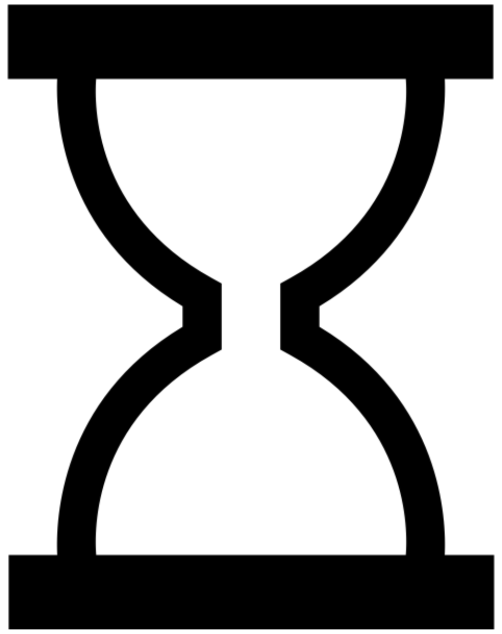
WHAT? Likert scale: 1-4

WHO? Domain experts: Designers

WHERE? In-house: Wix Studio


Job 1 - Designers
Job 2 - Visual experts
Job 3 - Students
FAIL

Do we ask questions correctly?



Velocity

Crowdsourcing Services

- Crowd Intelligence
- Custom Job Creation
- Ability to blacklist “bad” labelers
- Instant Feedback
- Price
- **FAIL FAST**

New Labeling Experiment

How would you rate this logo? (required)

- ○ Beautiful
- ○ Good
- ○ Bad
- ○ Ugly

New Labeling Experiment

Dicksons Family

B&B

Is the logo beautiful? (required)

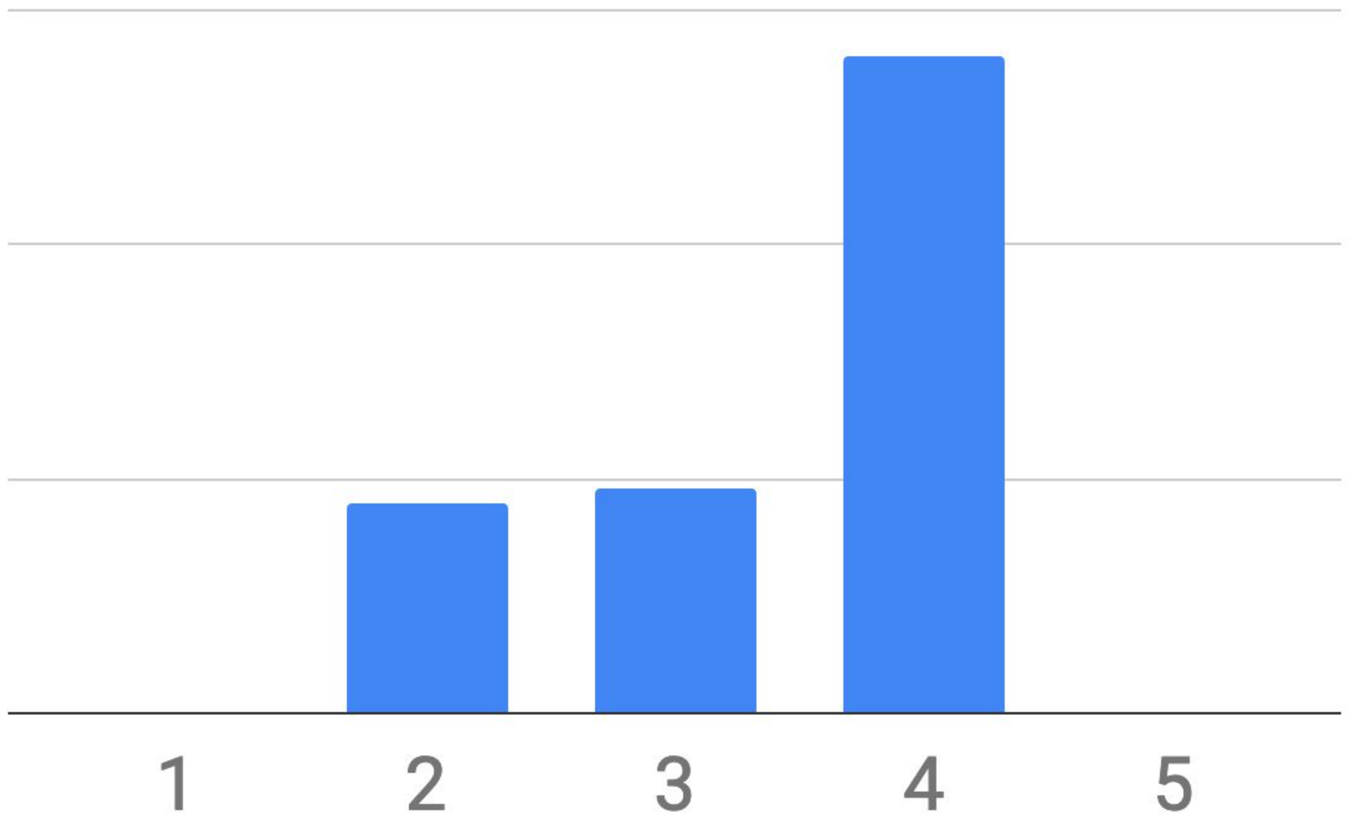
- ◯ Yes
- ◯ No

New Labeling Experiment

How would you rate the design of this logo from 1-5? (1=poor, 5=excellent)

- ◯ 5
- ◯ 4
- ◯ 3
- ◯ 2
- ◯ 1

New Labeling Experiment



Pairwise Comparison

A

B

Which logo is more beautiful? (required)

- ○ A
- ○ B

New Labeling Experiment Results

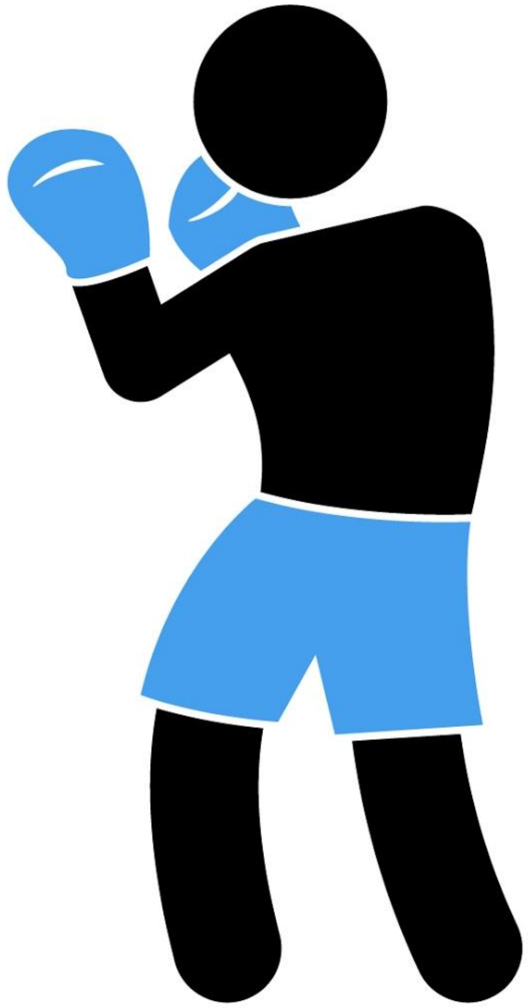
	Rank 1-5	Pairwise Comparison
Feedback Score (1-5)	2.4	**4.2**
% of Success	26%	**87%**
Time	11h	**6h**
Price	0.15$/logo	**0.11$/logo**

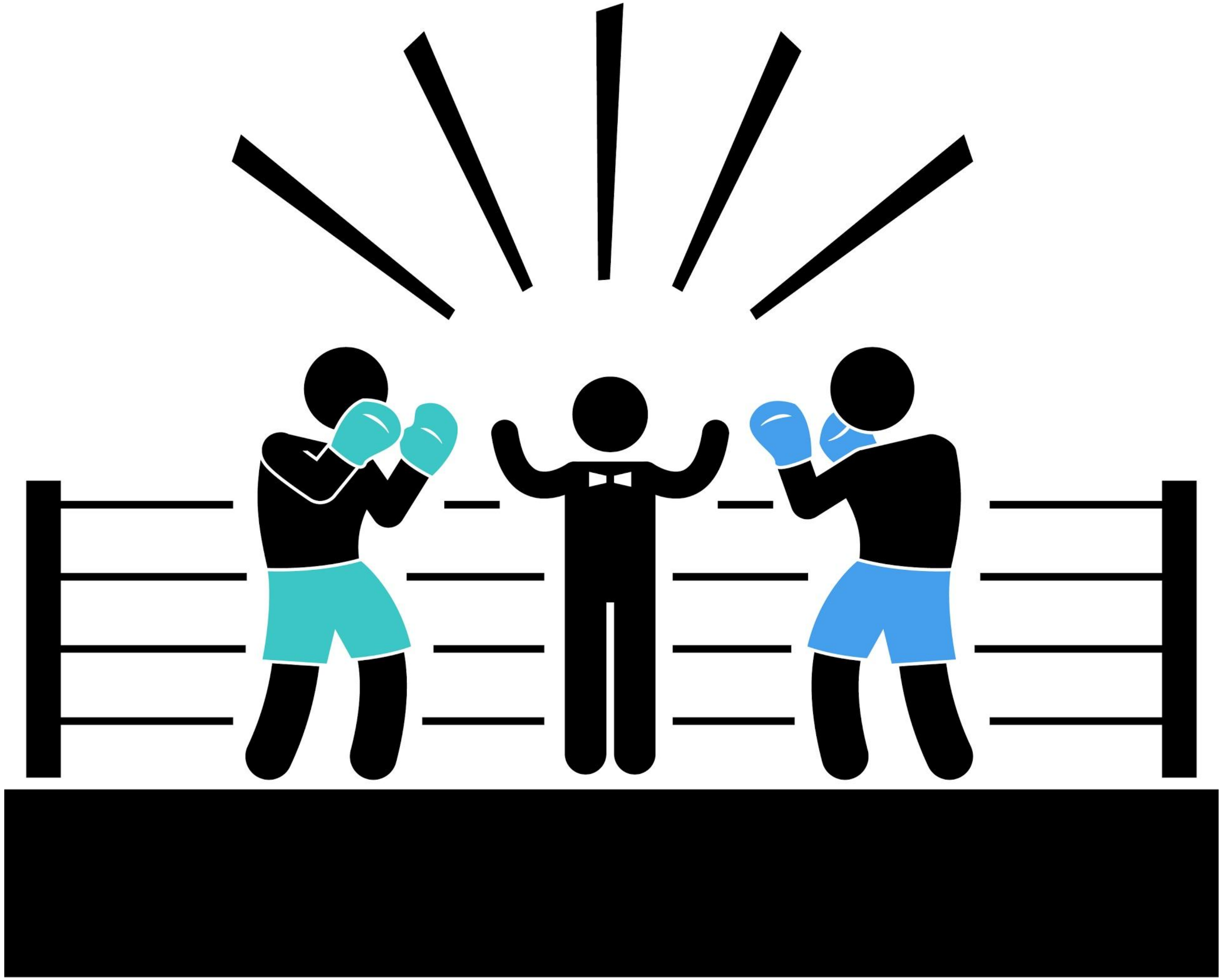
From Pairwise Comparison To Label

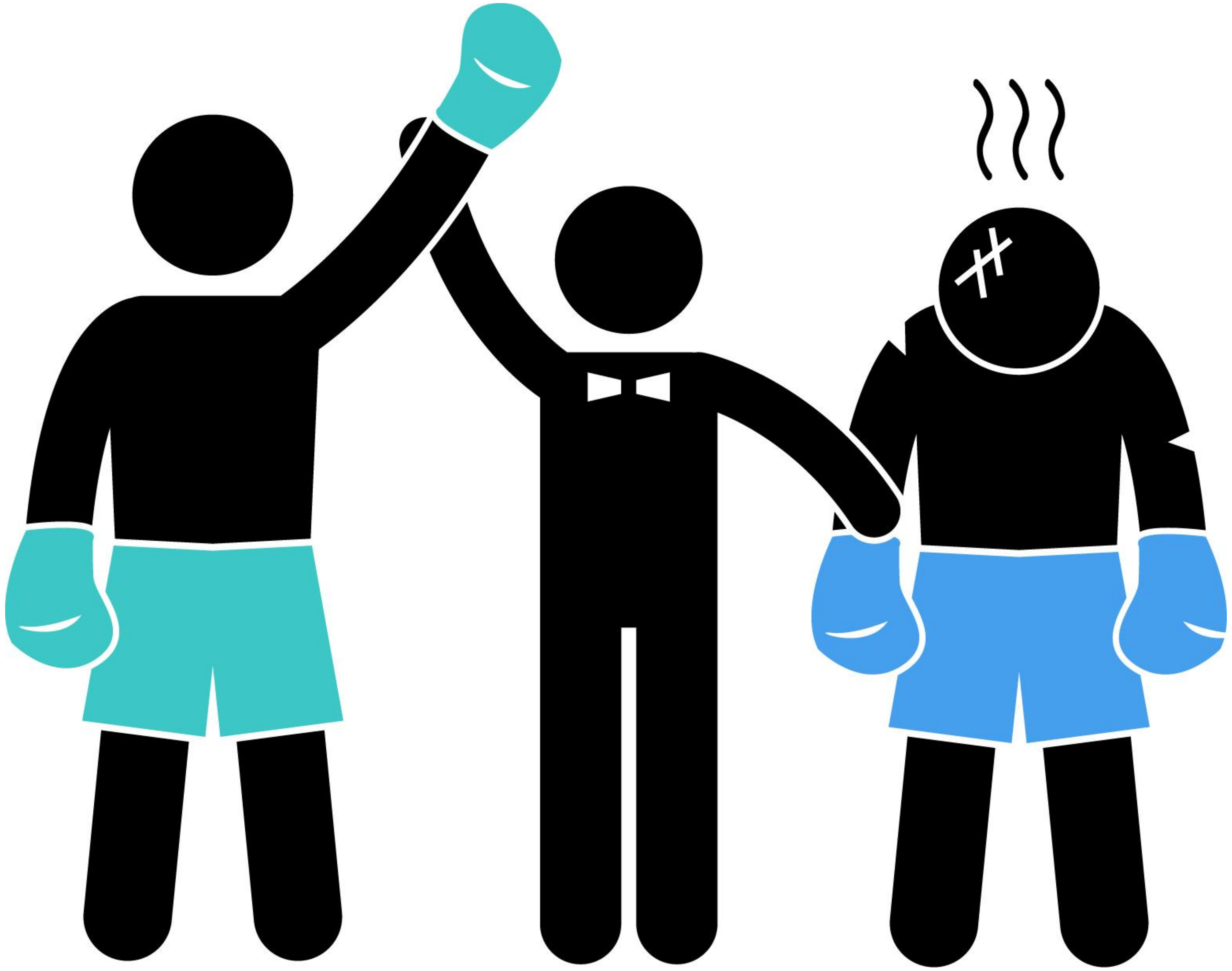
ELO Rating System - 1960

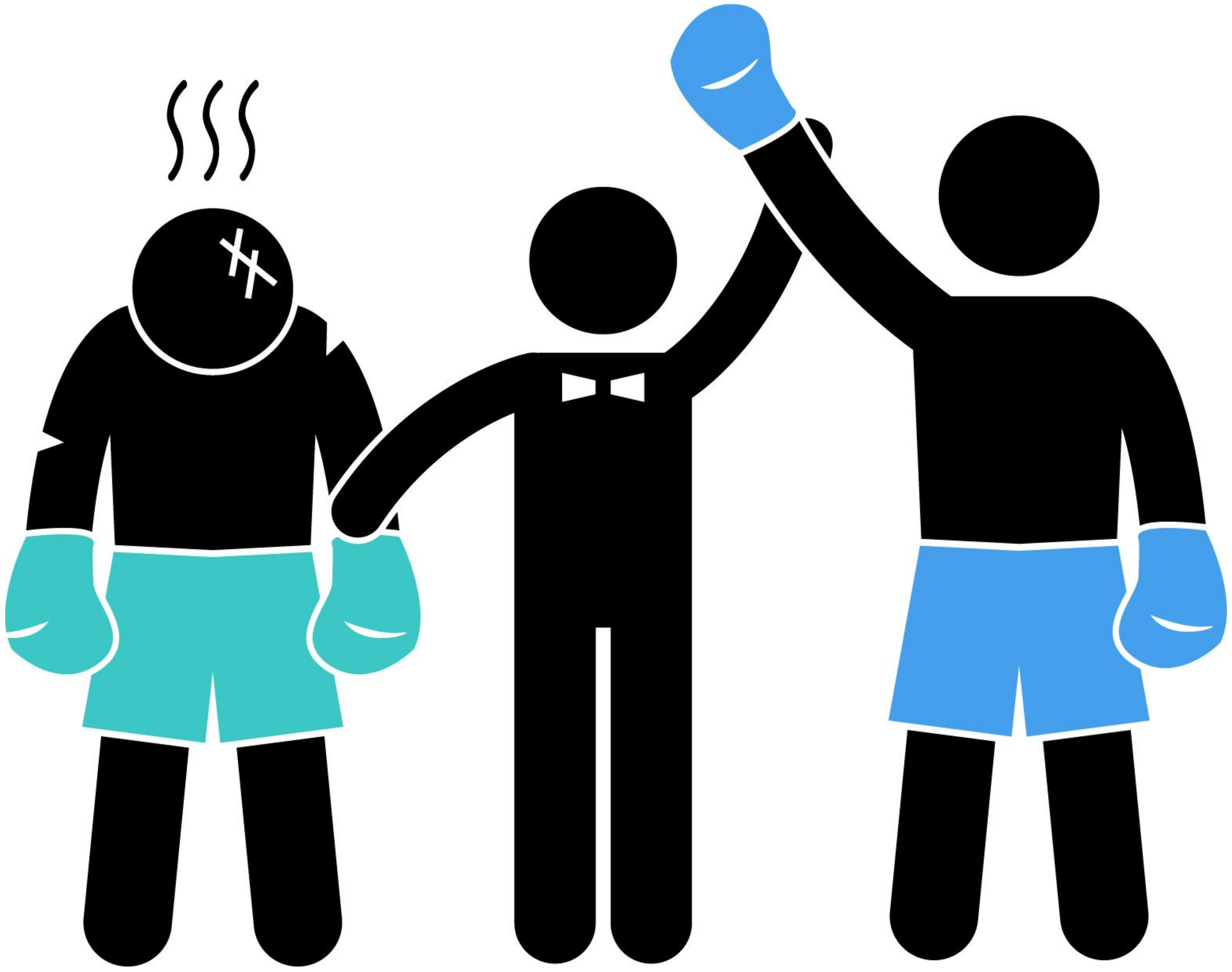
The difference in the ratings between two players serves as a predictor of the outcome of a match.

32	**Age**	25
50	**Fights**	15
50	**Won**	8
0	**Lost**	7
209cm	**Heights**	190cm









Elo Rating Logic

Step 1: Calculate expected outcome of the game

$$E_A = \frac{1}{1+10^{(R_B - R_A)/400}} = \frac{1}{1+10^{(50-100)/400}} = \frac{1}{1+0.74} = 0.57$$

$$E_B = \frac{1}{1+10^{(R_A - R_B)/400}} = \frac{1}{1+10^{(100-50)/400}} = \frac{1}{1+1.33} = 0.42$$

$$R_A = 100$$

$$R_B = 50$$

Step 2: Update the rating depending on the actual outcome of the game

$$R'_A = R_A + K(S_A - E_A) = 100 + 100(0 - 0.57) = 100 - 57 = 43$$

$$R'_B = R_B + K(S_B - E_B) = 50 + 100(1 - 0.43) = 50 + 57 = 107$$

,where **S** is the outcome of the match (1- won, 0 - lost, 0.5 - draw);

K - scaling value helps to control the amount of change that can occur per game

Pairwise Comparison - How to?

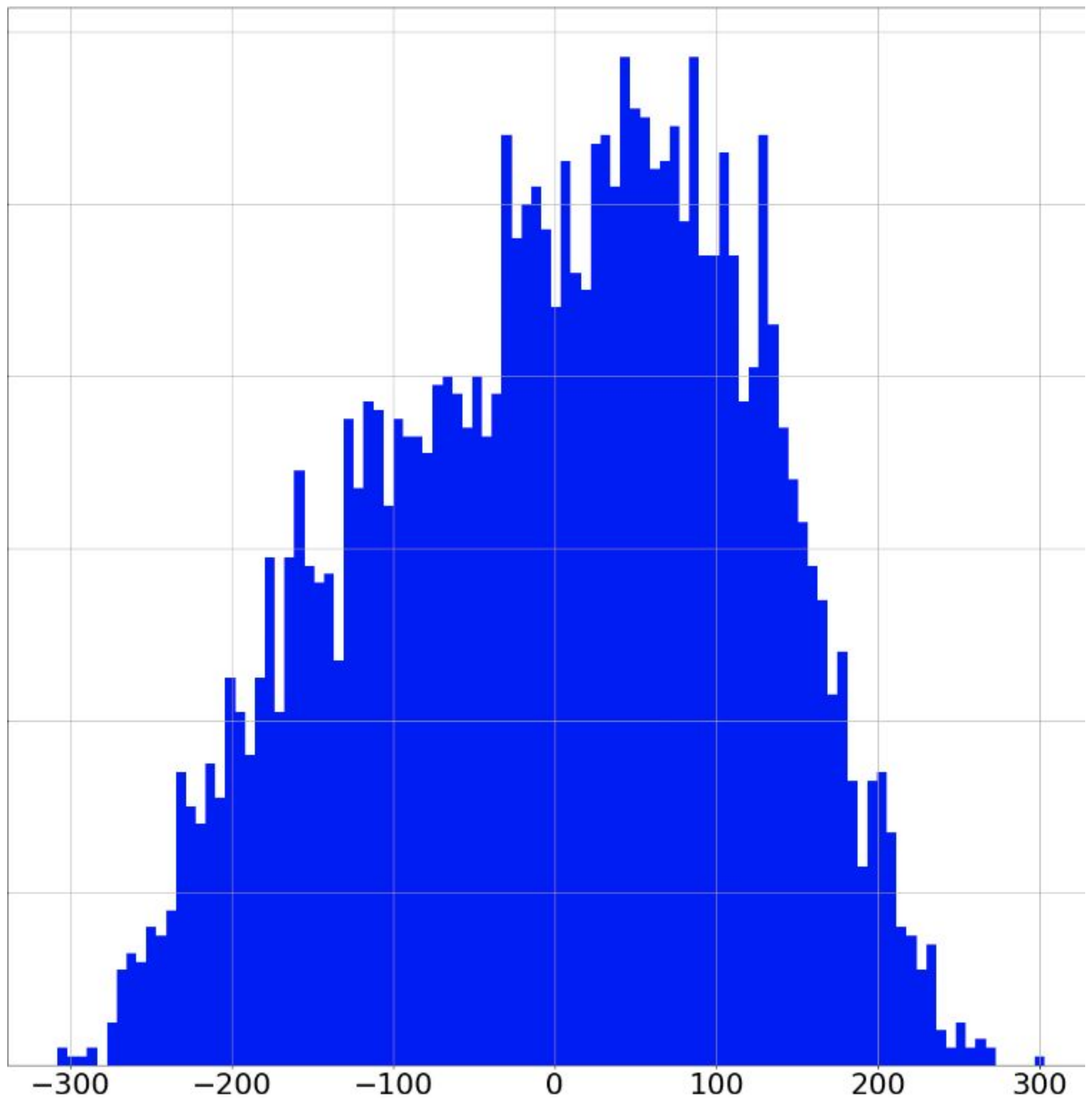
Number of pairwise comparisons with N candidates: O(N^2)

$$\frac{N(N-1)}{2} = \frac{1000(1000-1)}{2} = 499,500$$

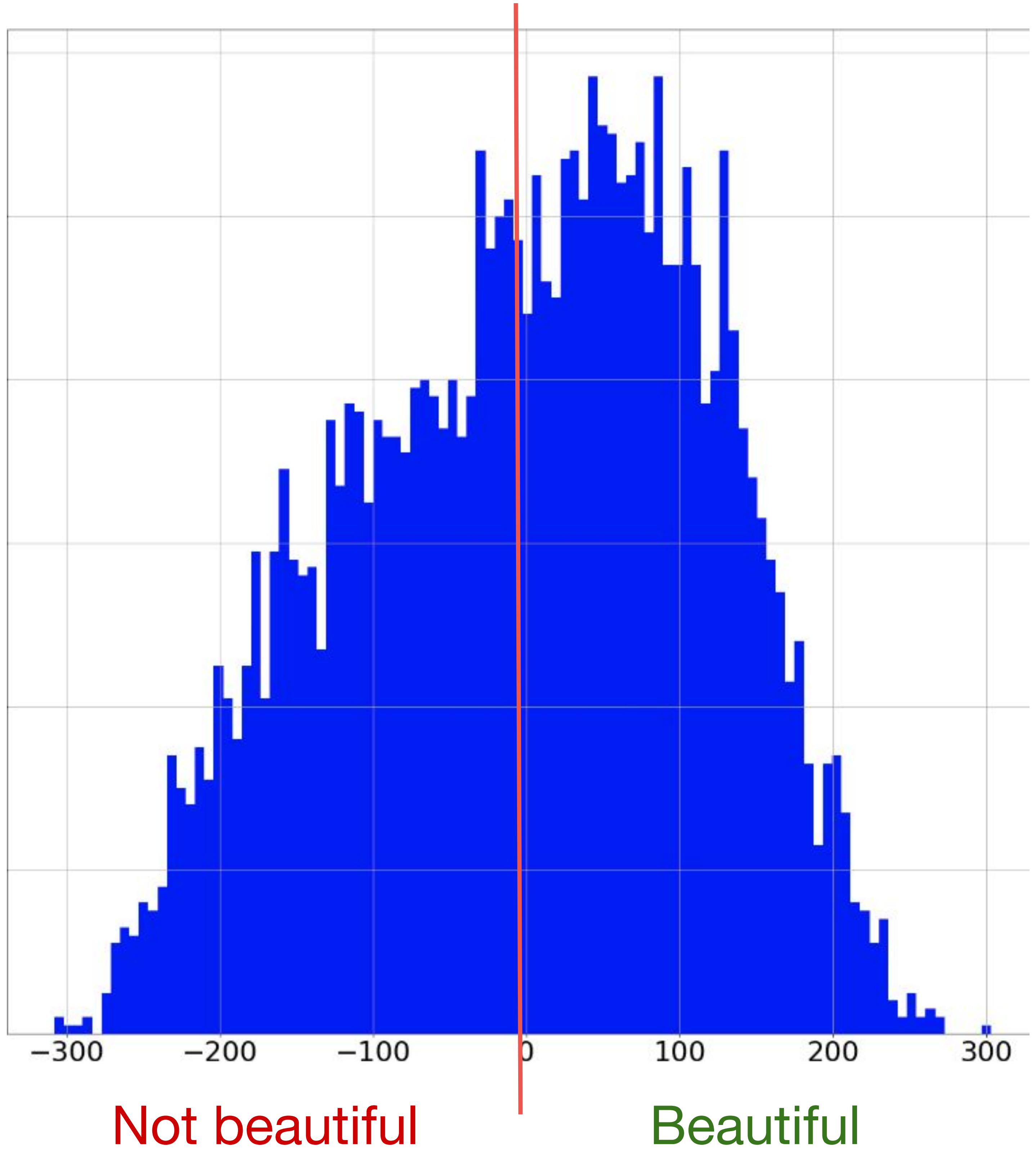
When using sorting algorithms, in our case Elo score, we are able to reduce the complexity to O(NlogN)

$$N\log_2 N = 1000\log_2 1000 = 9,956$$

ELO Rating Distribution



ELO Rating Distribution



Threshold:

0

F1 Score:

74.9

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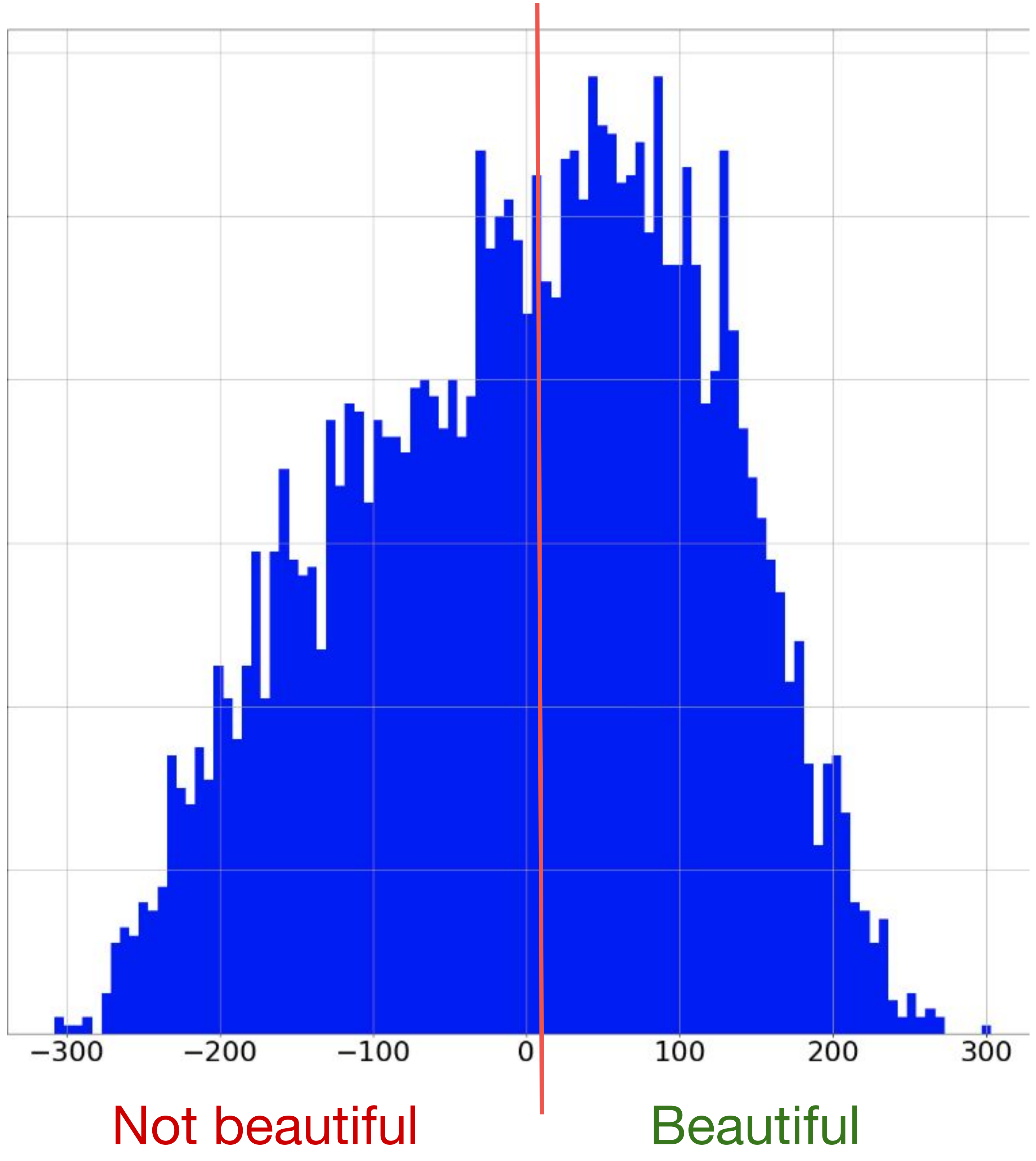
Can Machines Learn Beauty

ELO Rating Distribution



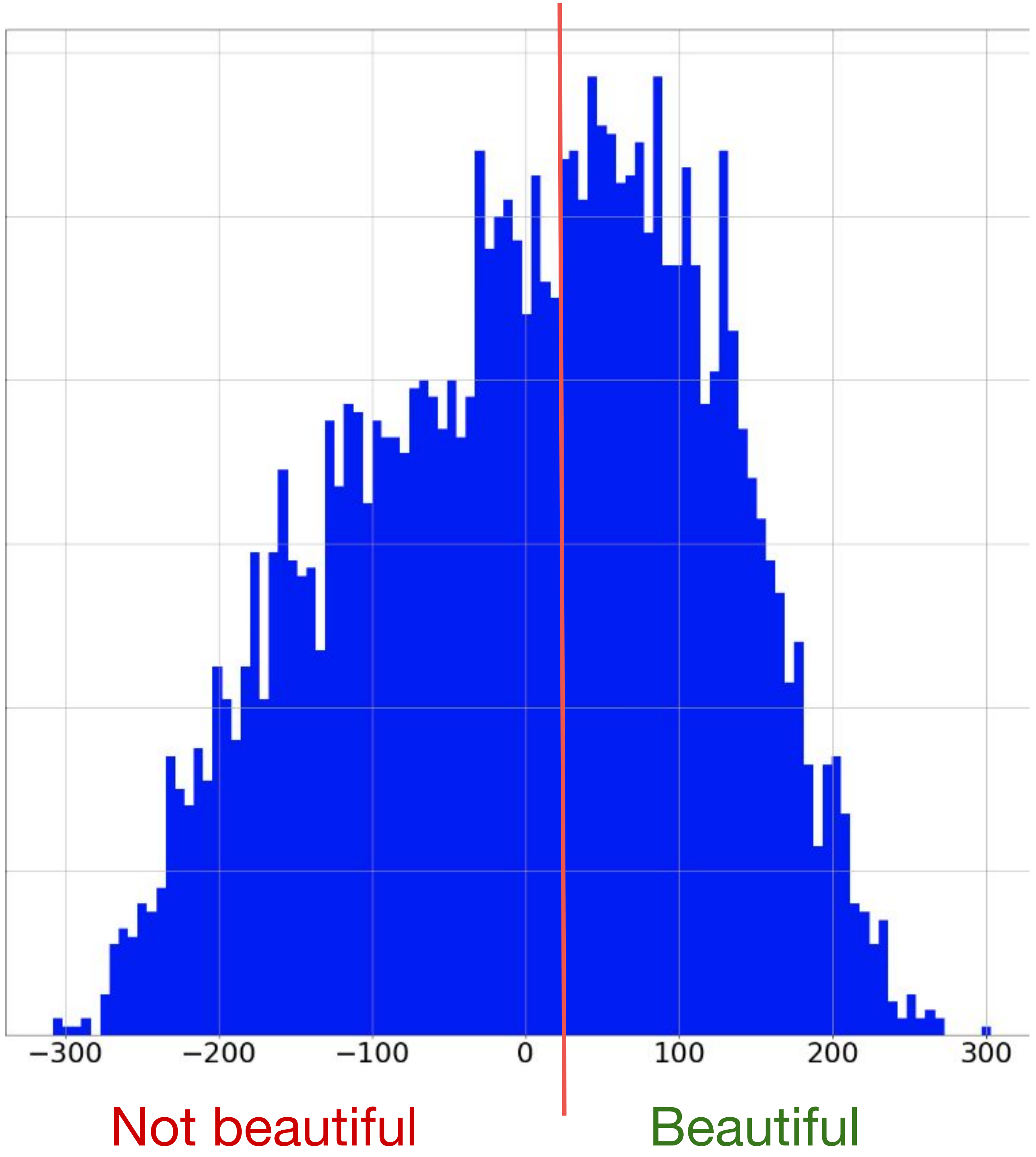
Threshold:

10

F1 Score:

74.6

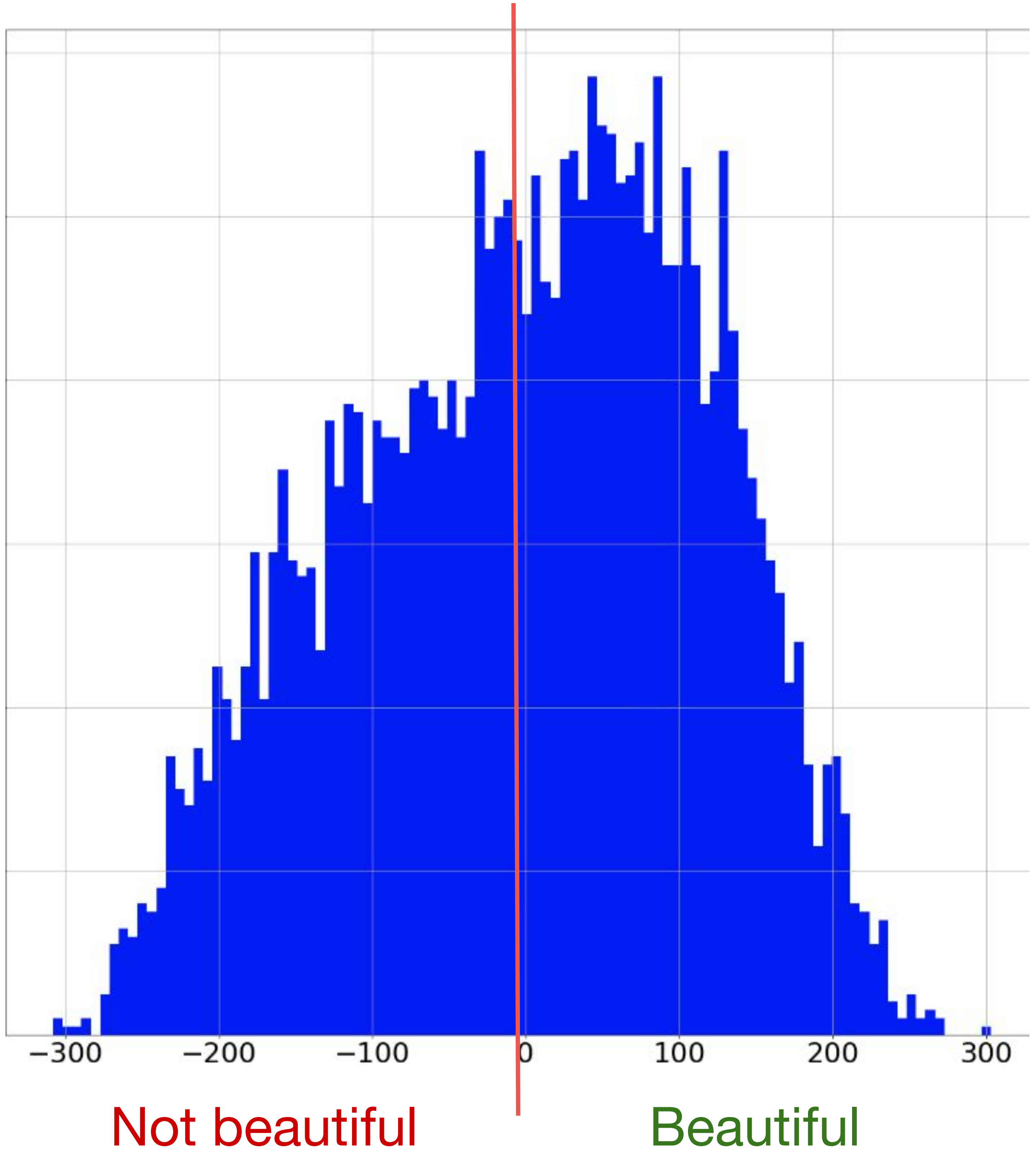
ELO Rating Distribution



Threshold:
20

F1 Score:
74.3

ELO Rating Distribution



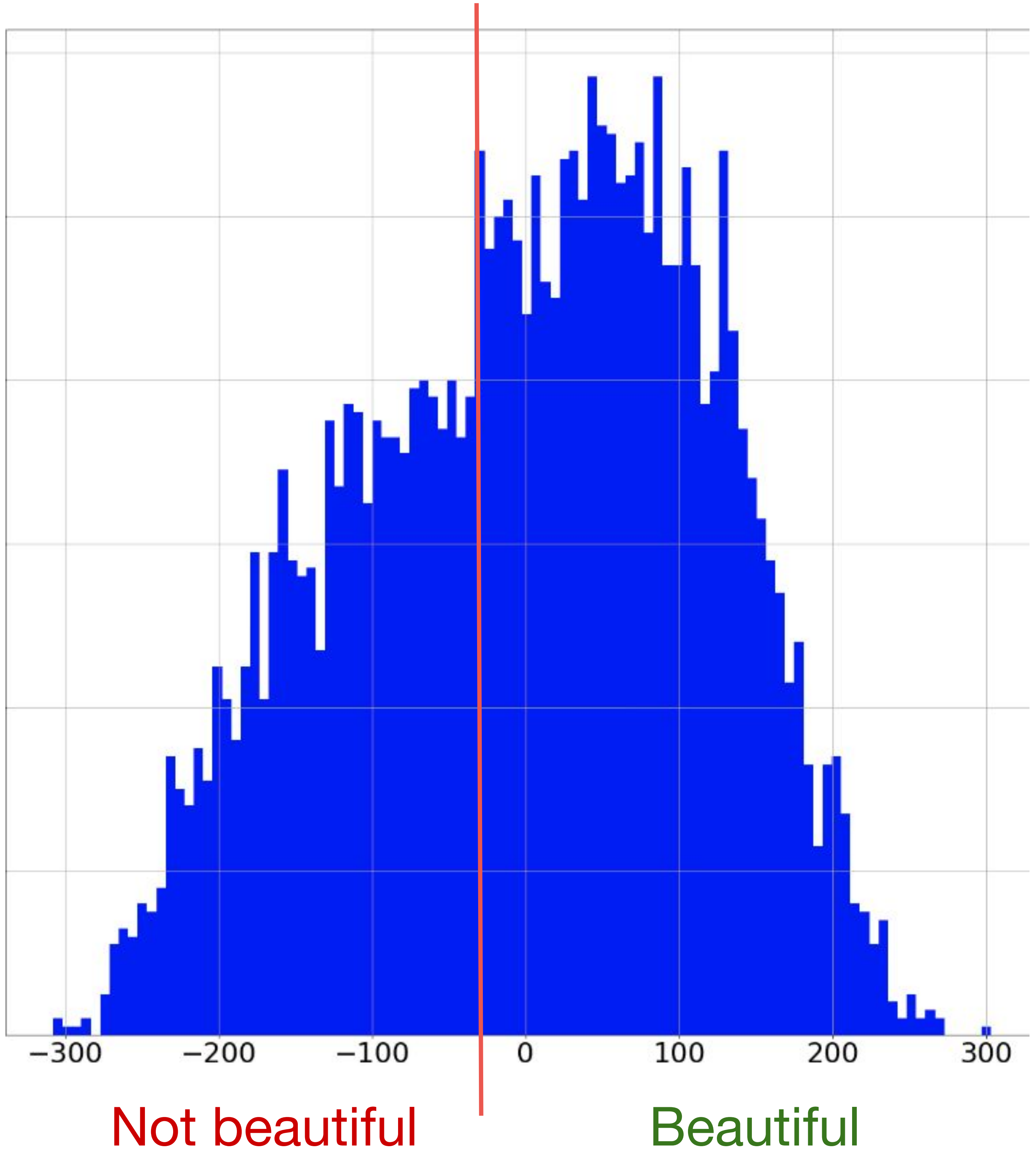
Threshold:

-10

F1 Score:

75.3

ELO Rating Distribution



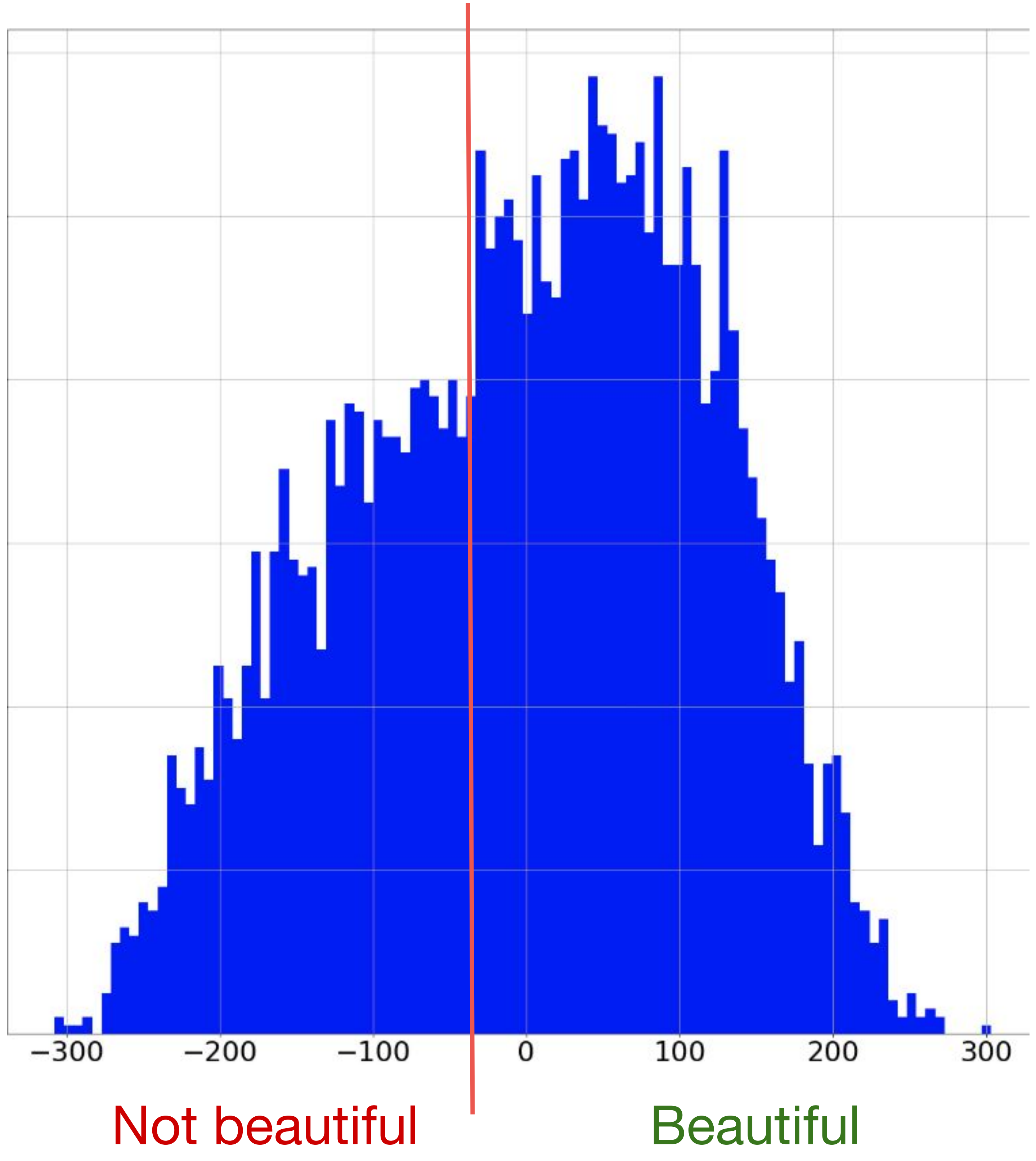
Threshold:

-20

F1 Score:

76.7

ELO Rating Distribution



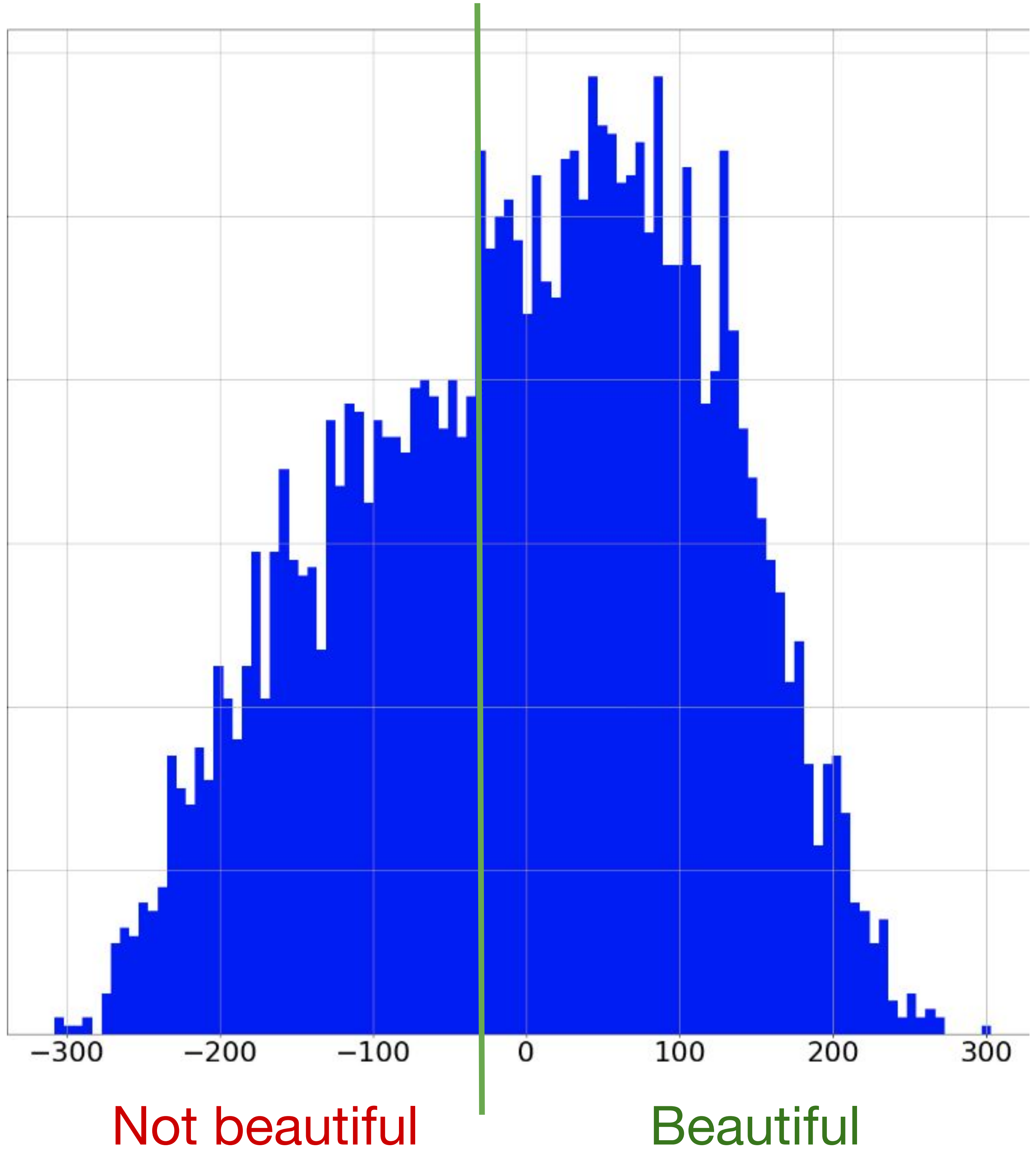
Threshold:

-30

F1 Score:

74.9

ELO Rating Distribution



Threshold:

-20

F1 Score:

76.7

Training Dataset

Not Beautiful

Reunion Of Hisar Veterinarians In North America
2019V01R

S B PLUMBING AND HEATING SERVICES
Plumbing

THE OFFICE OUTSOURCE COMPANY

At the Tones

Beautiful

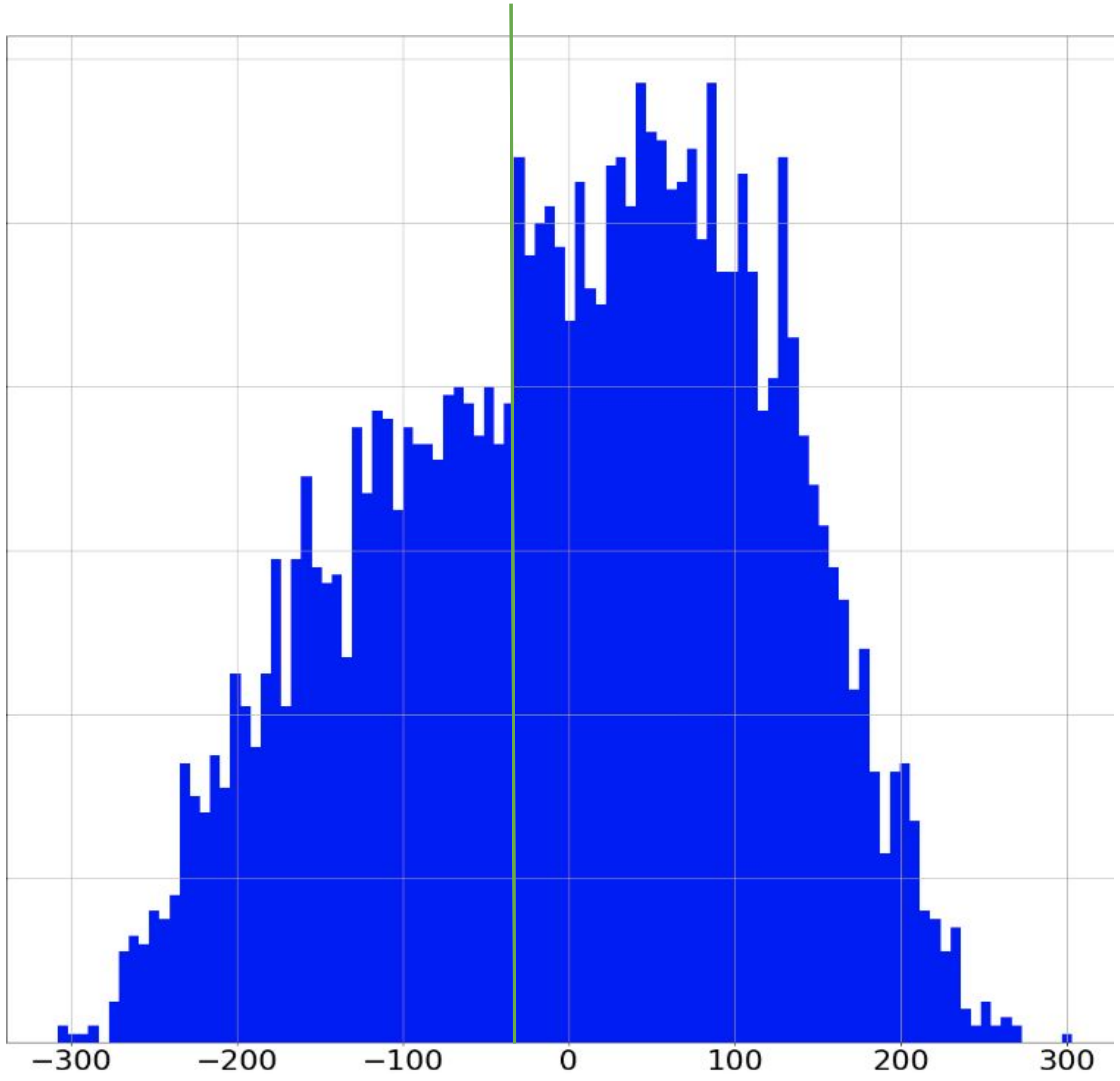
Ear Goddess

Ada B. Willow
Where Family Gathers

CARTHAGE TECHNOLOGIES
We built knowledge

Master Apparel
True style never dies

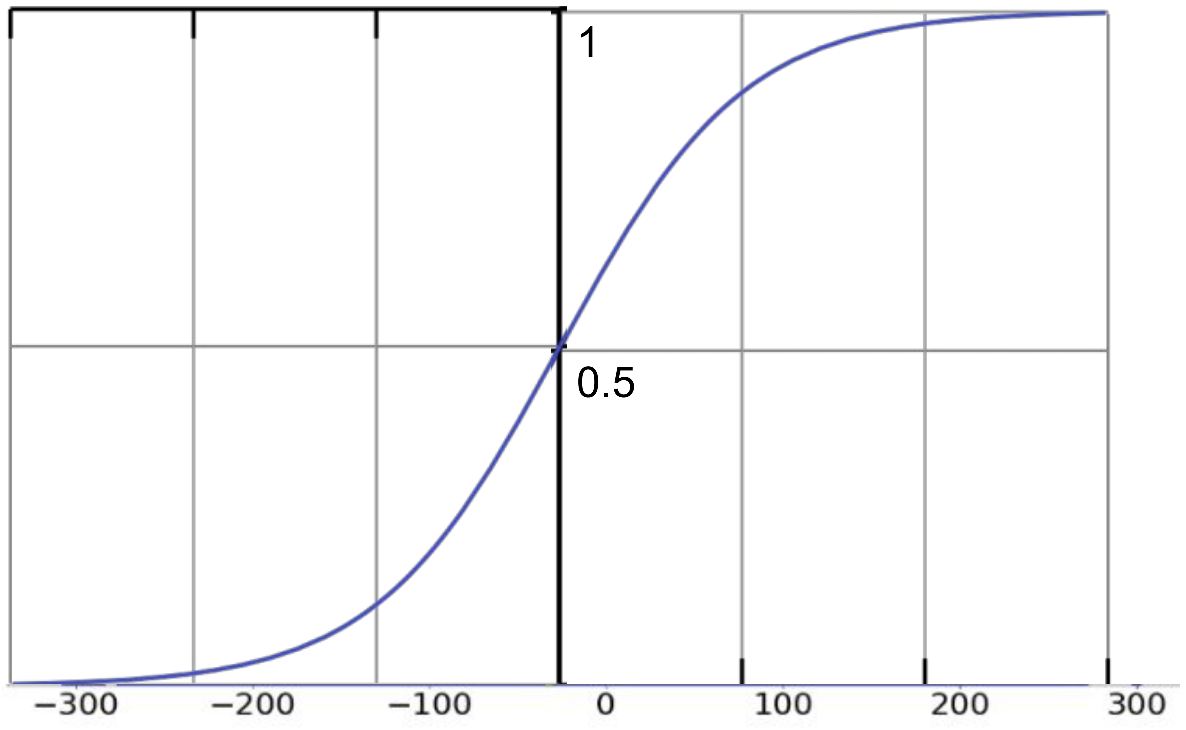
Sample Weight

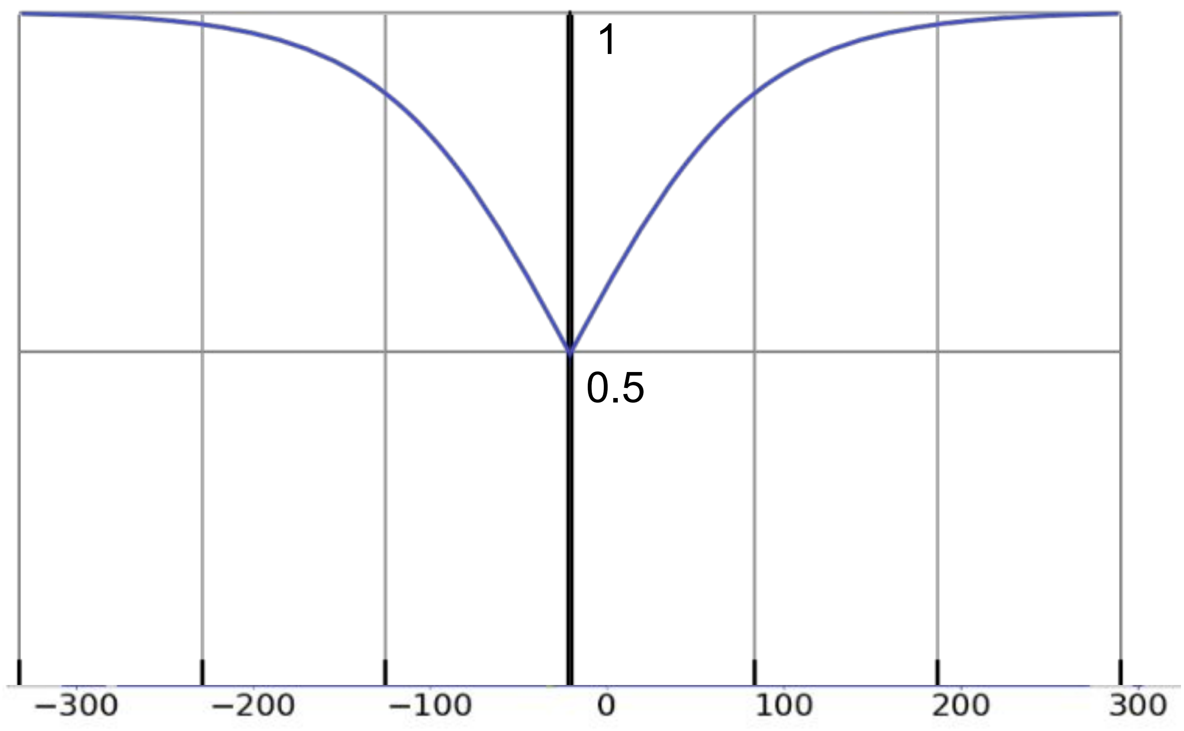


Not beautiful

Beautiful

Sample Weight





Not beautiful Beautiful

Not beautiful Beautiful

Feature Generation & Modeling

Cekap Solution

Berkesan Berpatutan dan Berbaloi


```
▼ object {2}
    logoId : 007fcec4-8487-4eec-91de-999de9aa09bd
  ▼ cords {3}
    ▶ icon {4}
    ▶ companyName {4}
    ▼ tagline {4}
        width : 192.90625
        height : 14.171875
        x     : 94
        y     : 34.375
```


Onboarding Information

Elements Properties

Generated Features

- Symmetry
- Alignment
- Proportions
- Aspect Ratio

has_icon	has_tagline	has_frame	icon_area	tagline_area	company_name_area	frame_area	icon_horizontal_symmetry_score
0	1	1	0	0.112993752	0.121884511	0.056152565	
1	1	0	0.34877725	0.049326412	0.174252467	0	3.86E-08
1	0	0	0.27035488	0	0.19482105	0	0

Model: XGBoost classifier

Result: F1 Score **86.2**

greatcopy.co.uk
Strong Language

DA DESIGNS
FURNITURE, CABINETRY & JOINERY

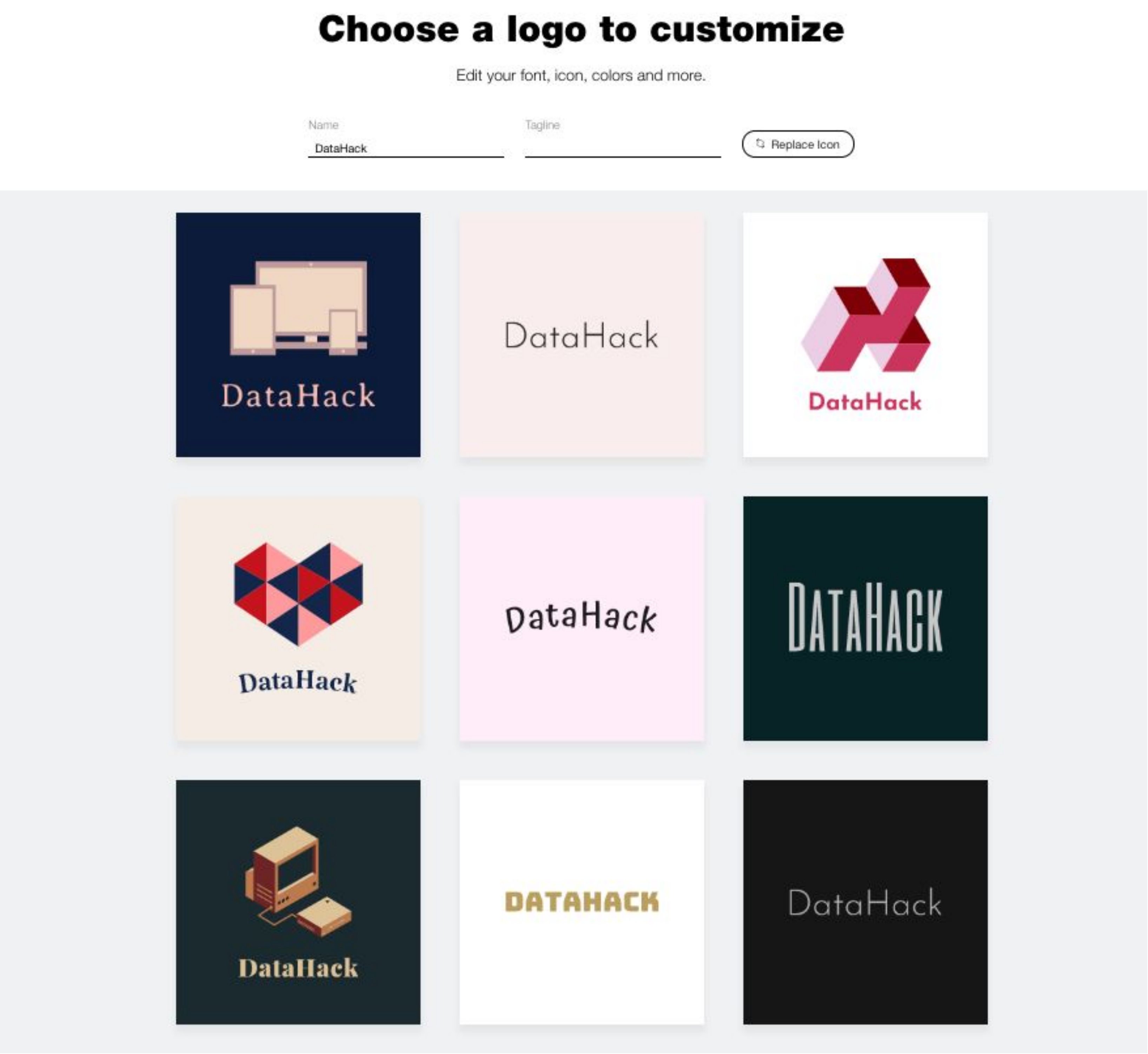
0 1

THE OFFICE OUTSOURCE COMPANY

MODUS
Consultancy Ltd

Going to Production (POC)

Presets Page



Presets Page determines the first impression of a customer with the Logo Maker

Presets Recommendation

Candidates	200 generated logos
Relevance	probability score of Beauty Prediction Model
Model	sorted list of logos based on the relevance score

WIX
Website Builder

WIX
Website Builder

WIX
Website Builder

WIX
Website Builder

WIX
Website Builder

WIX
Website Builder

Presets Recommendation

Candidates 200 generated logos

Relevance probability score of Beauty Prediction Model

Model sorted list of logos based on the relevance score

Flaw similar logos will be positioned next to each other

Presets Recommendation

Candidates	200 generated logos
Relevance	probability score of Beauty Prediction Model
Diversity	calculate Maximal Marginal Relevance (MMR)
Model	sorted list of logos based on the MMR score

MMR - Combining Relevance & Diversity

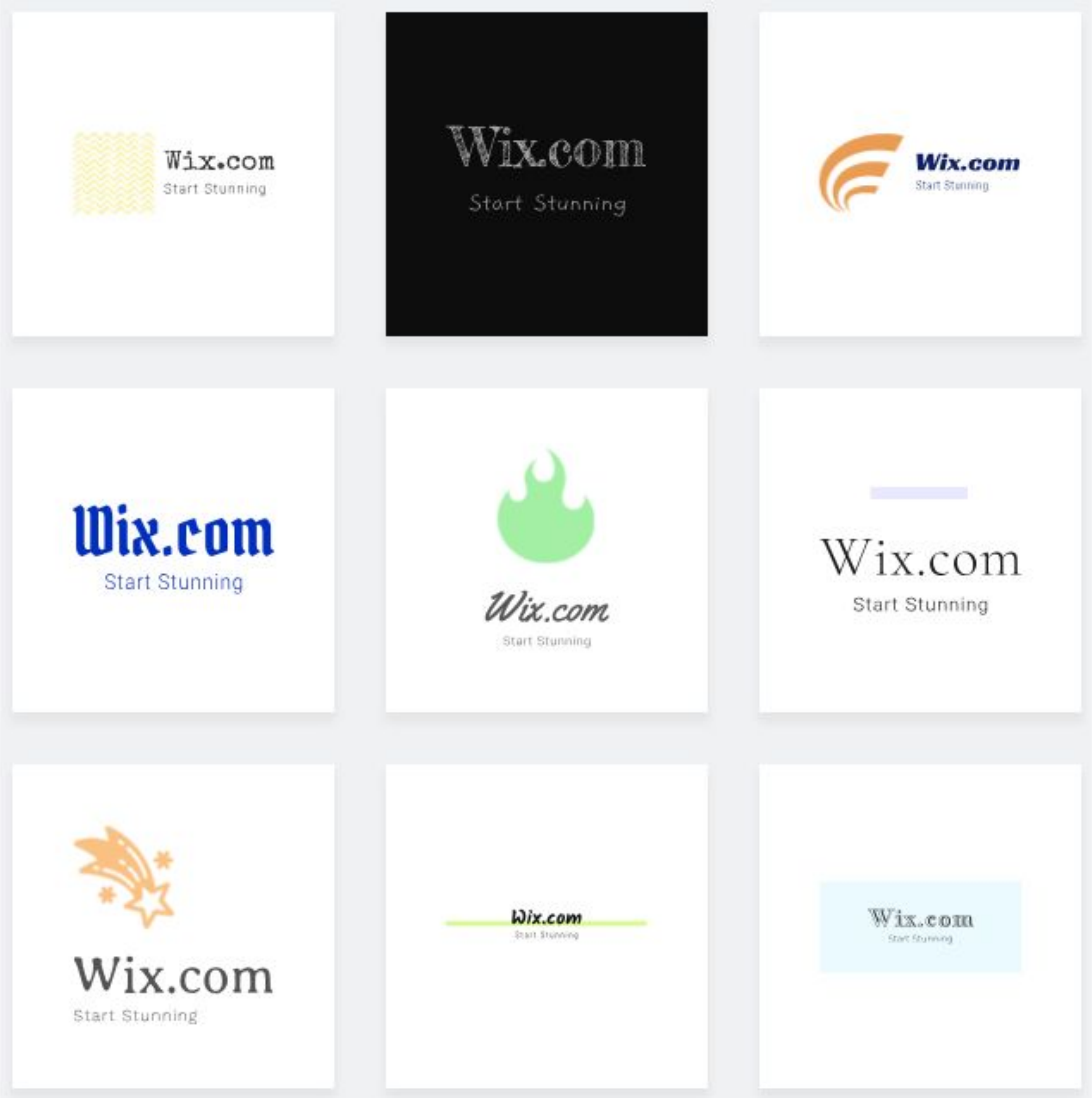
$$\text{MMR} = \arg\max_{D_i \in R \setminus S} \left[\lambda \boxed{\text{Sim}_1(D_i, Q)} - (1 - \lambda) \boxed{\max_{D_j \in S} \text{Sim}_2 (D_i, D_j)} \right]$$

Relevance
(Prediction Probability)

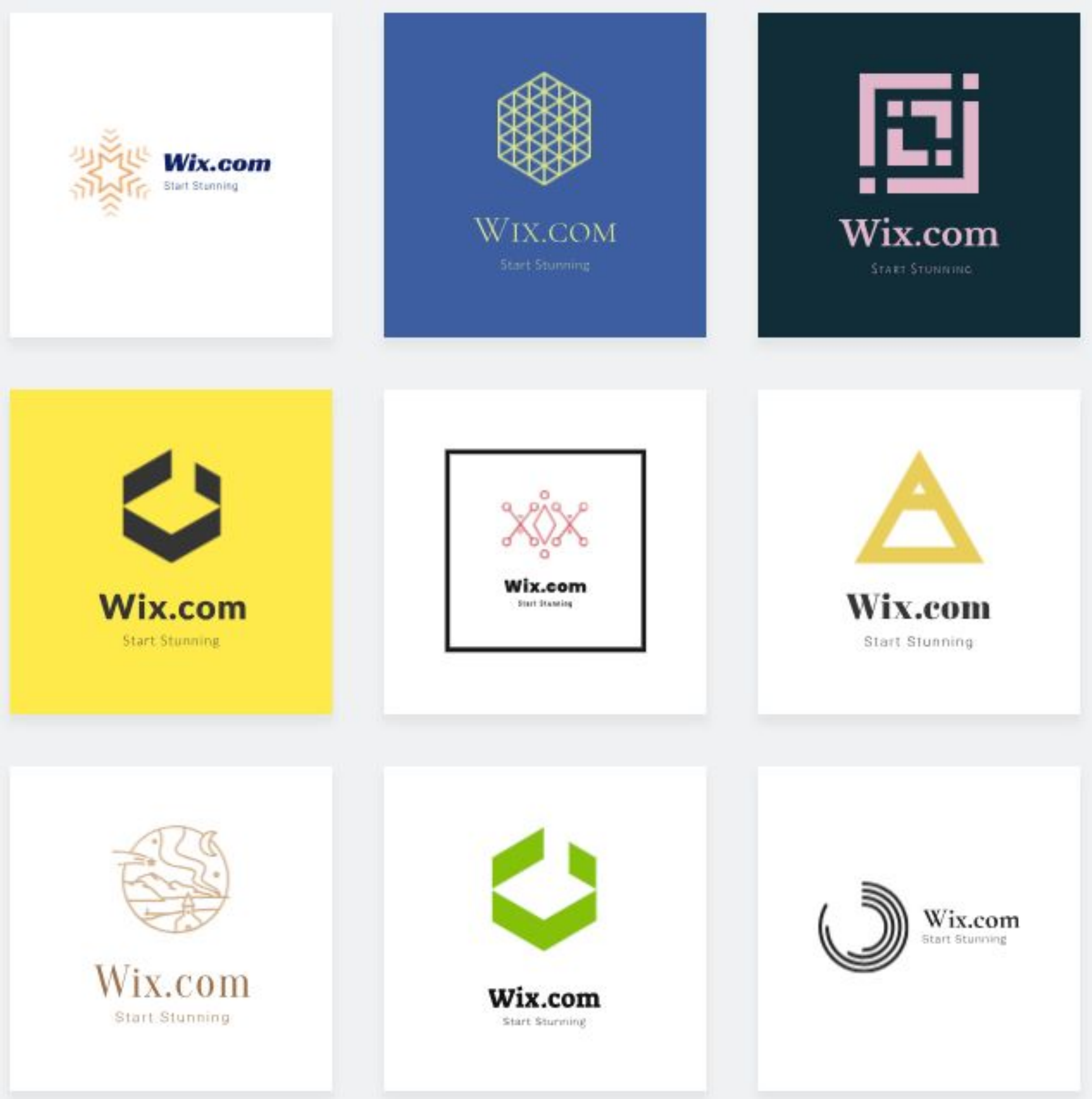
Diversity
(Cosine Similarity between presets)

- High λ = Higher Relevance
- Low λ = Higher Diversity

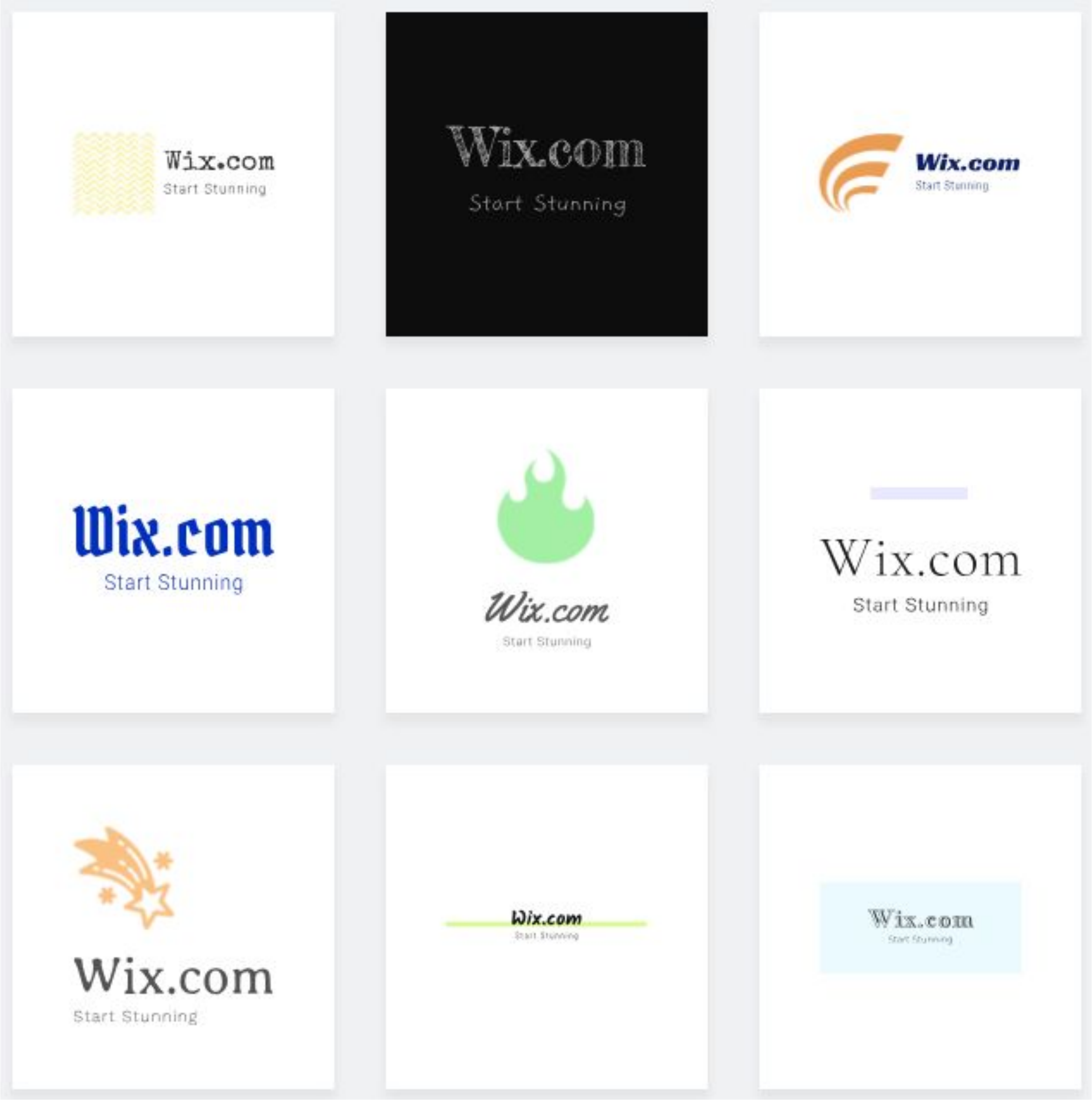
___ SORTING



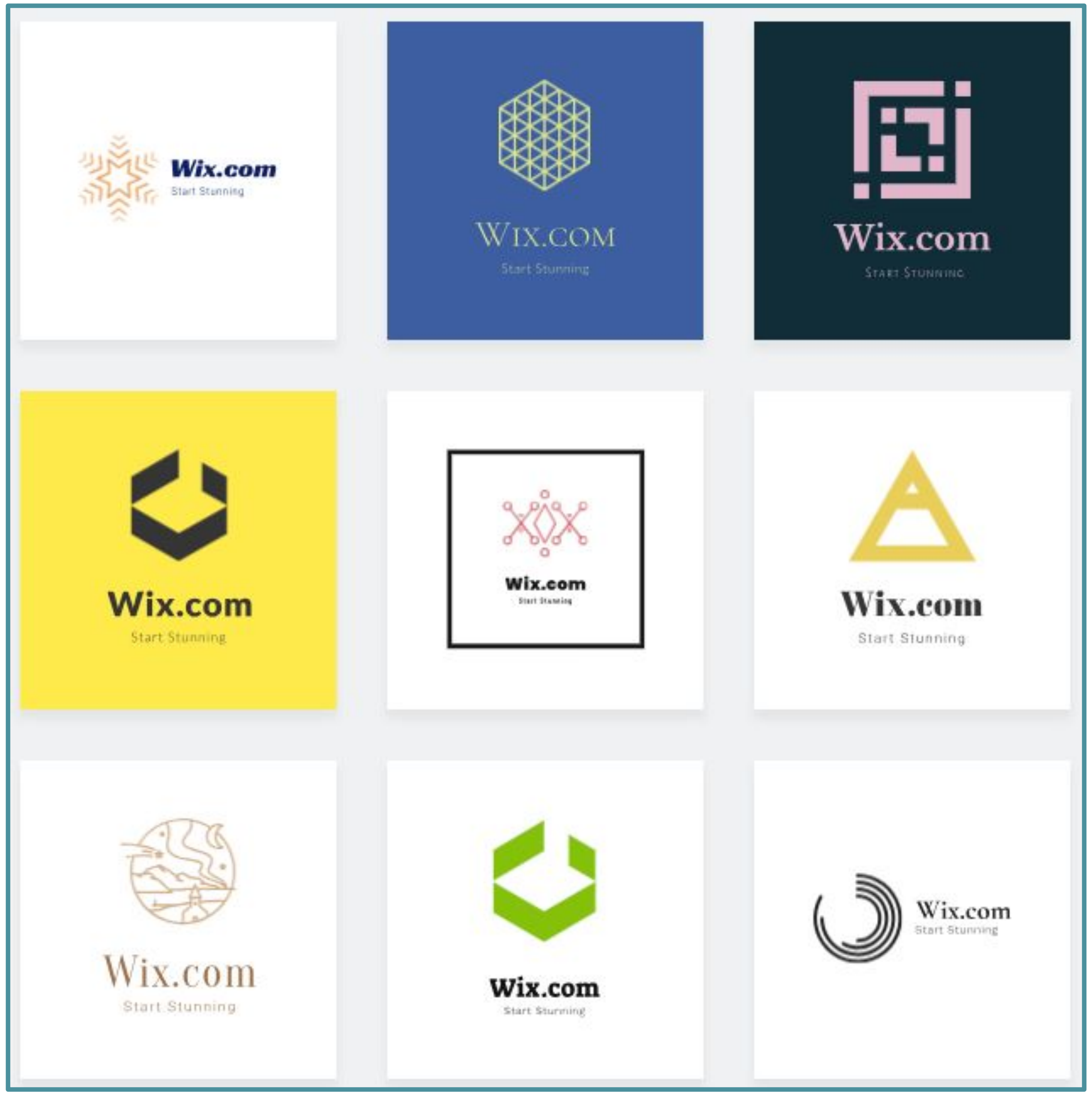
___ SORTING



OLD SORTING



NEW SORTING



But Does It Really Work?

YES!!!

And it's just the beginning...

Lessons Learned

Machines can learn anything, but we people aren't always good teachers

Test your assumptions

Fail, fail again and fail better...

Questions?

Thank You!

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