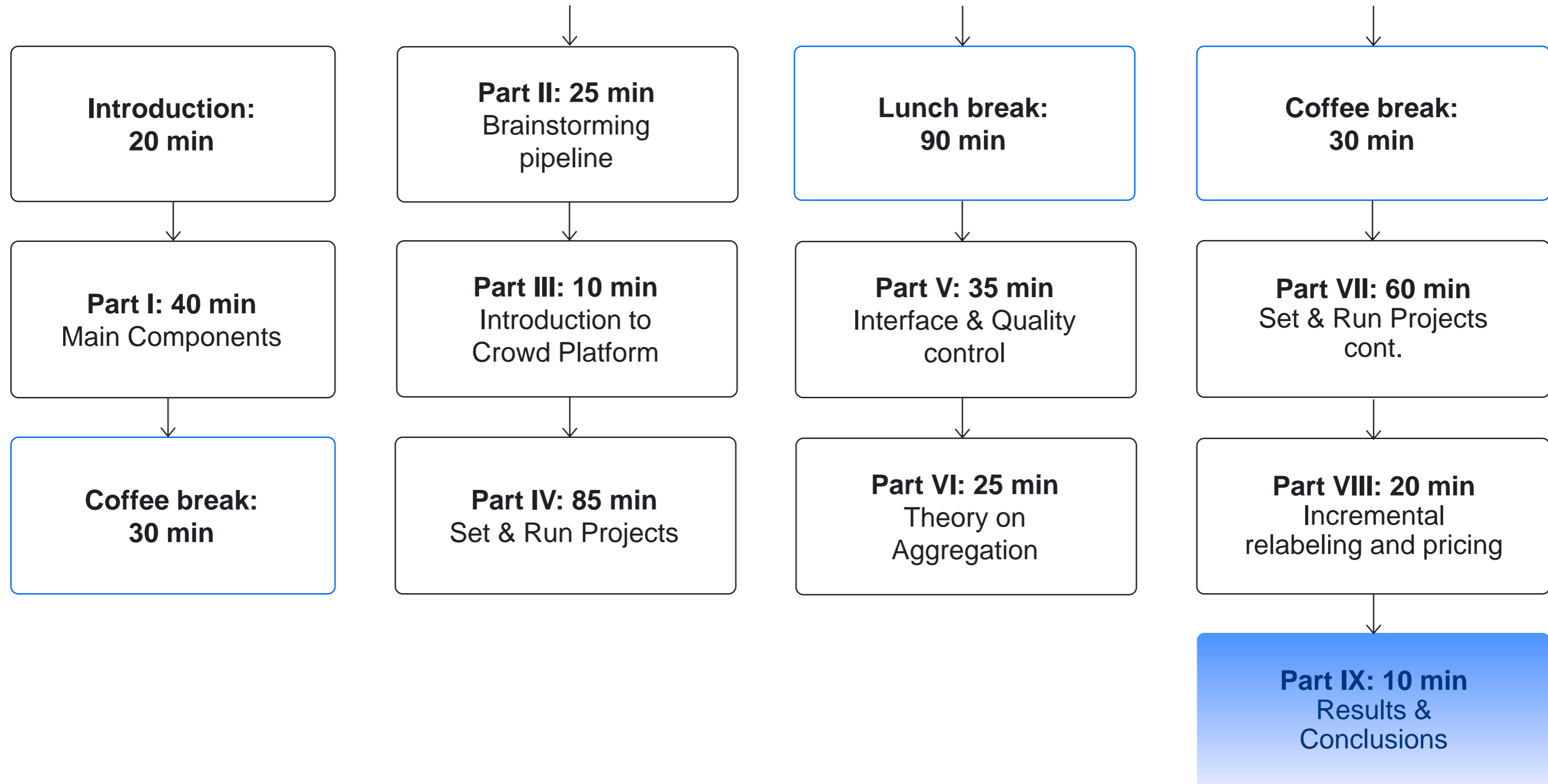


Part IX

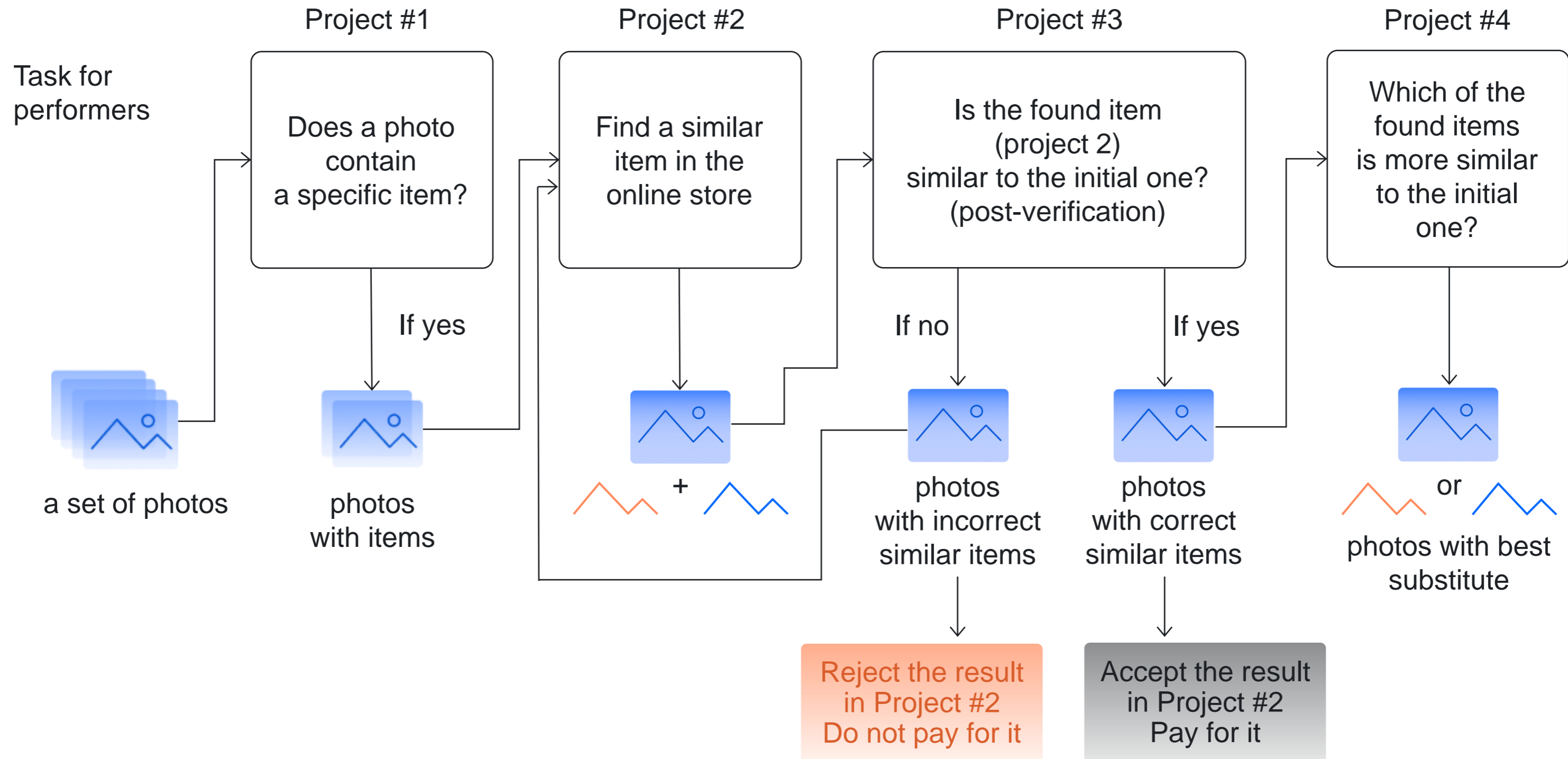
Discussion of the projects' results. Conclusions

Alexey Drutsa,
Head of Efficiency and Growth Division, Toloka

Tutorial schedule



Reminder: we implemented this pipeline



Project #1: Filter out photos without objects

Task

- ▶ Does a photo contain an item of desired type?

Our results

- ▶ Amount: 30 photos
- ▶ Overlap: 3
- ▶ Time: 5 min
- ▶ Cost: \$0.09 + Toloka fee



Are there **shoes** in the picture?

Yes No Picture not found

Project #2: Searching for similar items on the online store

Task

- ▶ Find a similar item on the internet

Our results

- ▶ Amount: 25 photos
- ▶ Overlap: 3
- ▶ Time: 25 min
- ▶ Cost: \$1.74 + Toloka fee



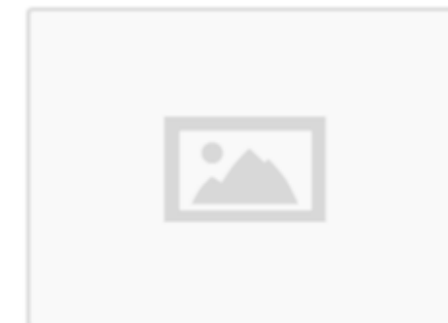
Find the same **shoes** on ASOS

ASOS

Shoes must be the same color and the same style.

Paste the link here

Upload the image here. The image should show the shoes you found.



Project #3: Accept correctness of items found

Task

- ▶ Is the found item (project 2) similar to the initial one?

Our results

- ▶ Amount: 75 photos
- ▶ Overlap: 3
- ▶ Time: 3 min
- ▶ Cost: \$0.20 + Toloka fee



Check that the uploaded image matches the product in the store.

[Check the item](#)

Are these **shoes** similar to each other?

Shoes must be the same color and the same style.

Yes No

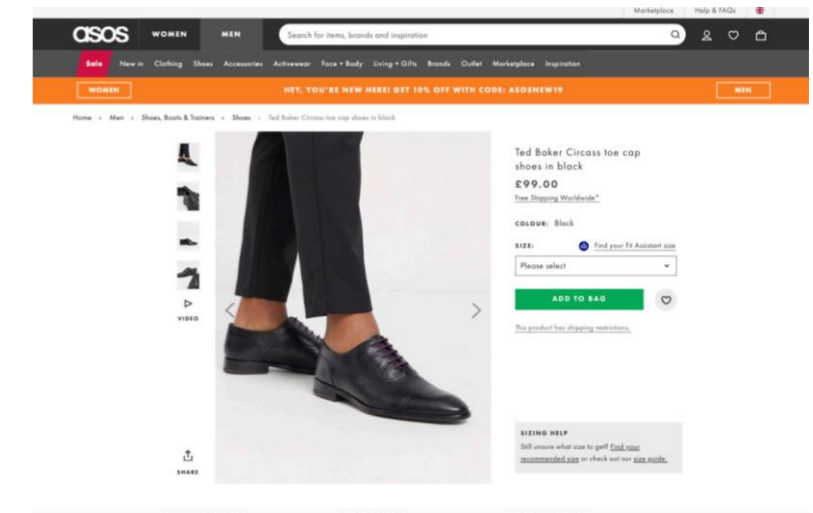
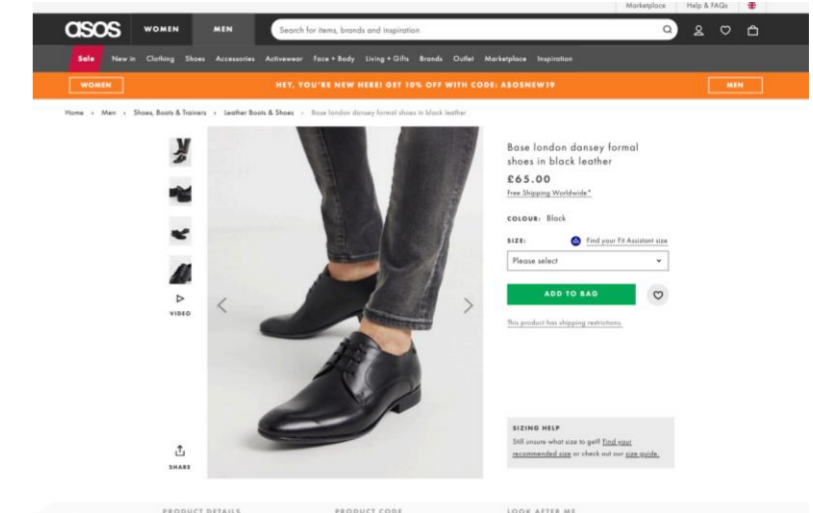
Project #4: Decide which substitute works best

Task

- ▶ Which of the items is similar to the initial one?

Our results

- ▶ Amount: 62 photos
- ▶ Overlap: 3
- ▶ Time: 10 min
- ▶ Cost: \$0.10 + Toloka fee



Statistics over the whole pipeline

- ▶ 30 photos processed to find the substitute items and evaluate their similarity
- ▶ Within 45 min on real performers
- ▶ Total cost: \$2.15 + Toloka fee

Afterparty: upgrade your pipeline

To obtain more comprehensive data

- ▶ Use more item types at the same time

To reduce costs

- ▶ Use incremental relabeling aka Dynamic overlap

To improve quality

- ▶ Use dynamic pricing
- ▶ Add more Golden Sets and hints
- ▶ Experiment with aggregation methods
- ▶ Add training for performers

API of Toloka

Allows you to automate all steps of our pipeline

▶ Discover at:

<https://yandex.com/dev/toloka/>

Crowdsource all types of data

Search Relevance

Moderation

Generation of content

Computer vision

Speech Technologies

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