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SIGMOD 2020 hands-on tutorial

Crowdsourcing Practice for Efficient Data Labeling: Aggregation, Incremental Relabeling, and Pricing

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Part VII

Discussion of the projects' results

Conclusion

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Yandex.Toloka is a service of Swiss company Yandex Services AG

Tutorial schedule

Introduction: 15 min

Part I: 20 min
Main Components

Part II: 10 min
Introduction to Crowd Platform

Part III: 15 min
Brainstorming pipeline

Part IV: 60 min
Set & Run Projects

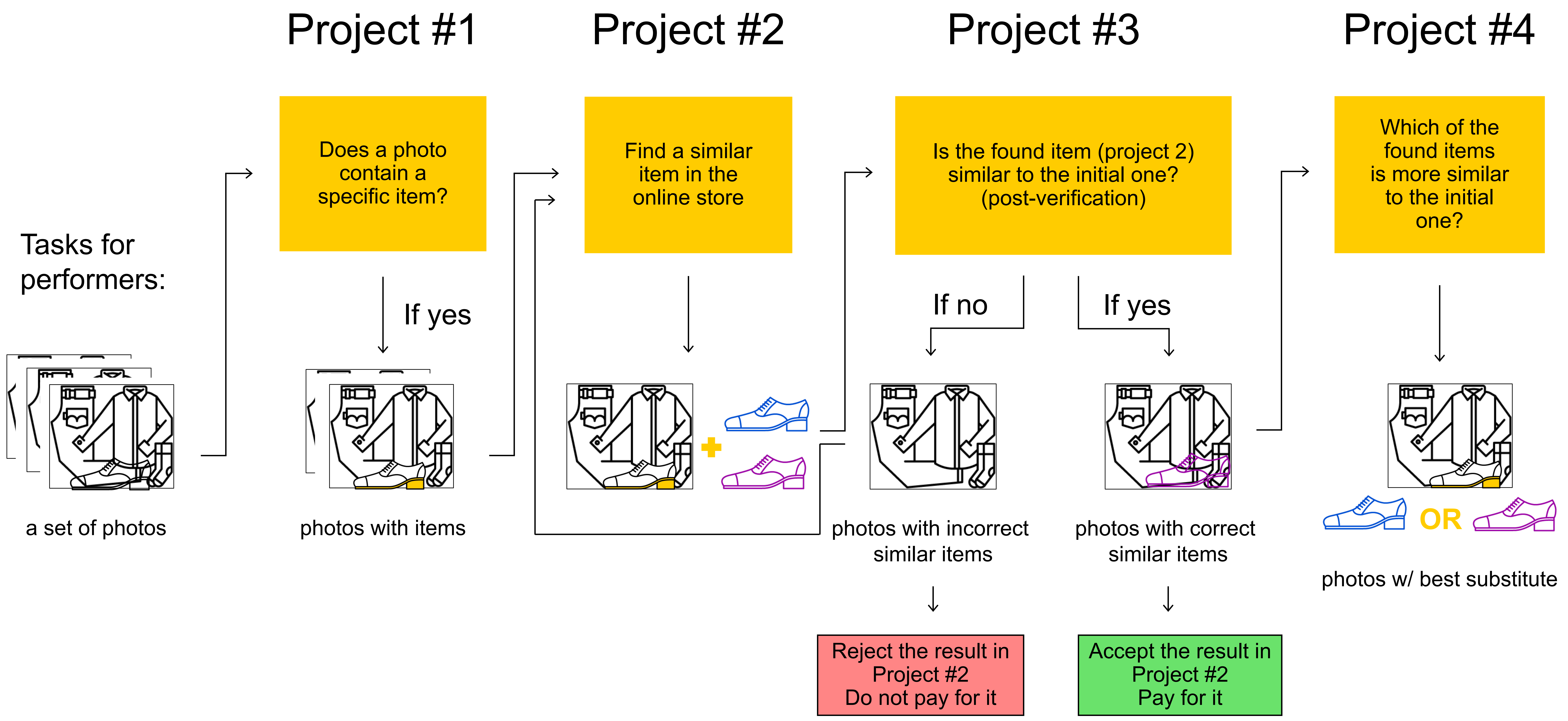
Part V: 25 min
Theory on Aggregation

Break:
30 min

Part VI: 20 min
Set & Run Projects cont.

Part VII: 10 min
Results & Conclusions

Reminder: we implemented this pipeline



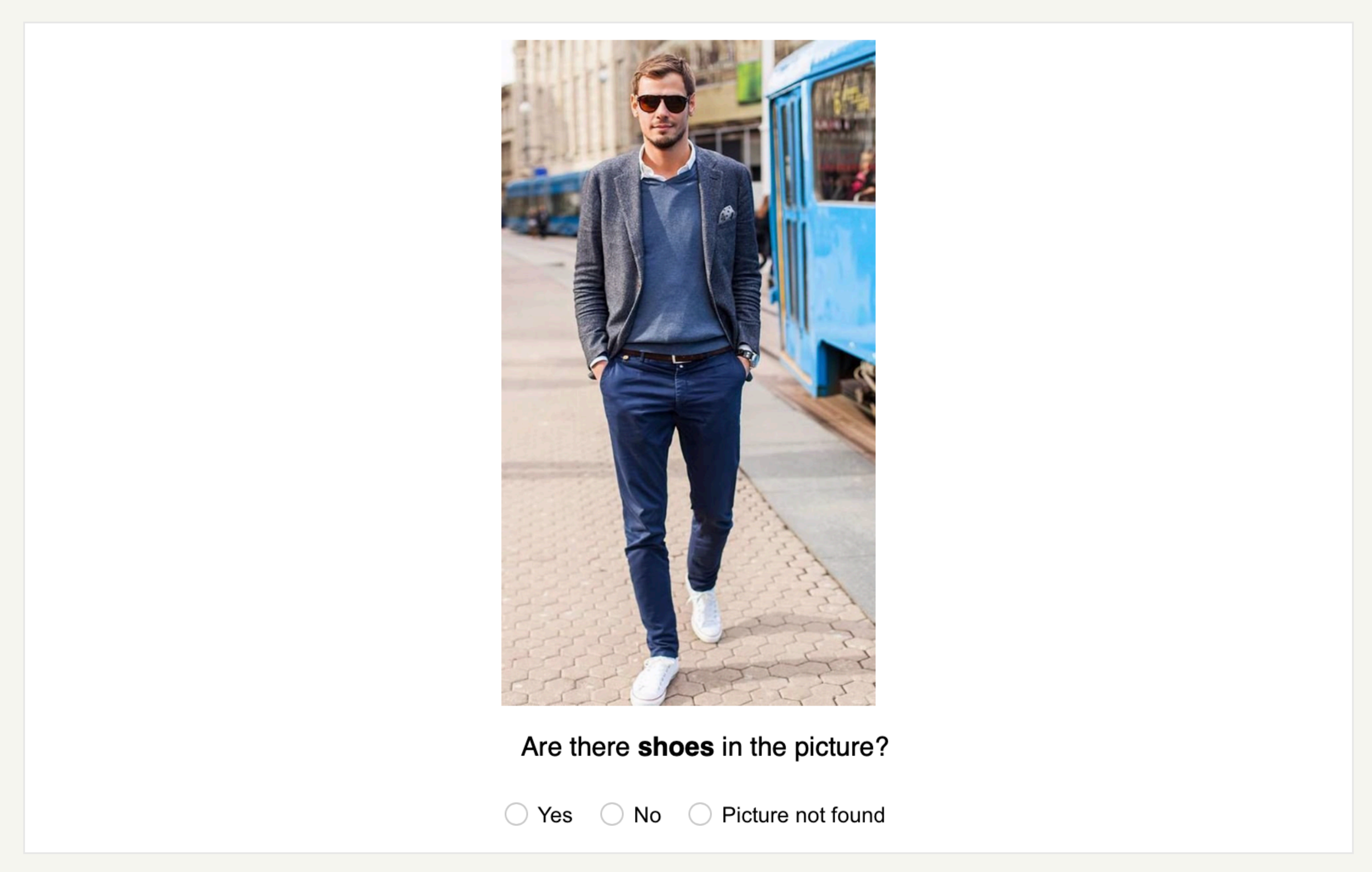
Project #1: Filter out photos without objects

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



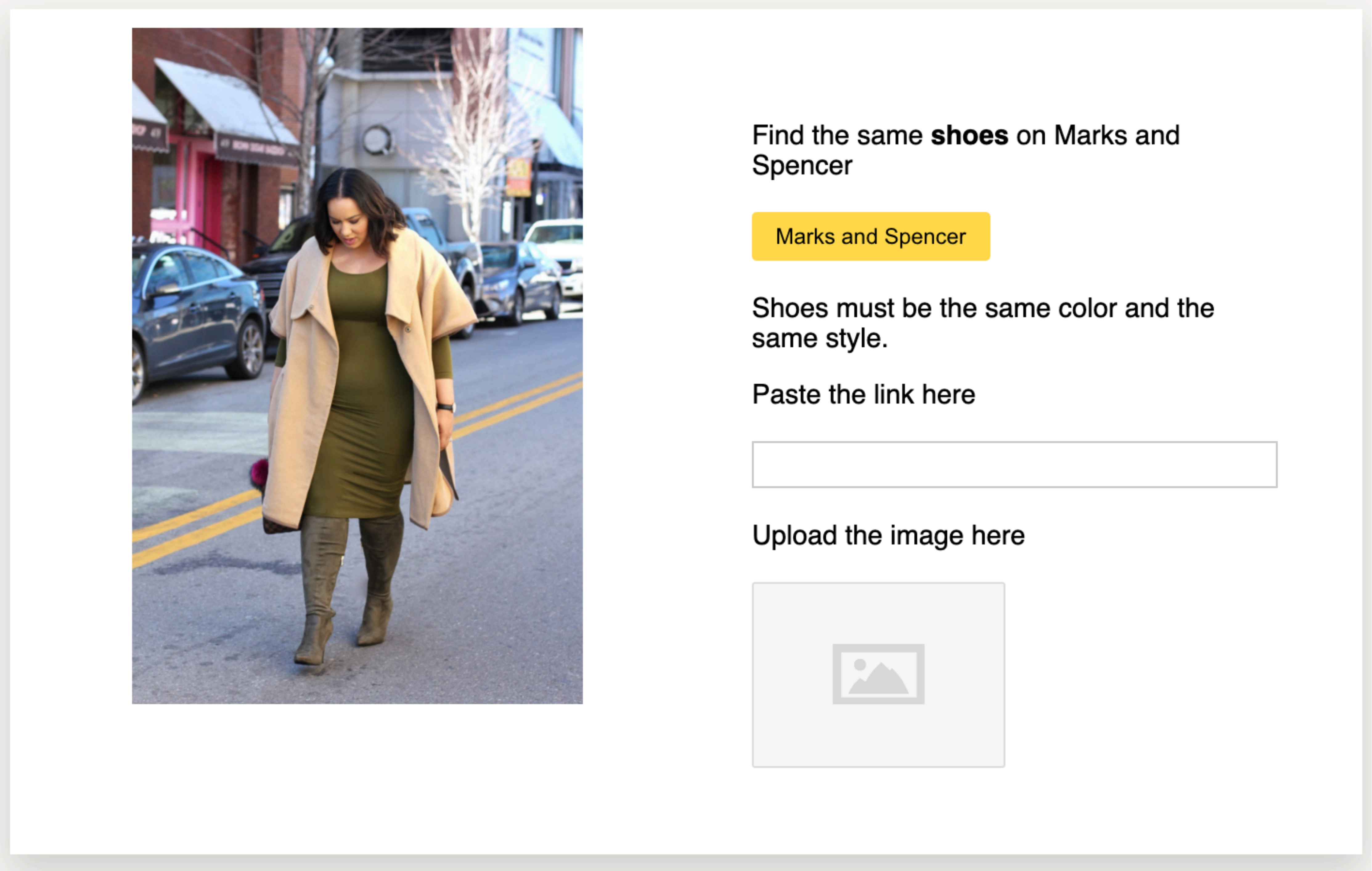
Project #2: Searching for similar items on the online store

Task

- Find a similar item on the internet

Our results

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



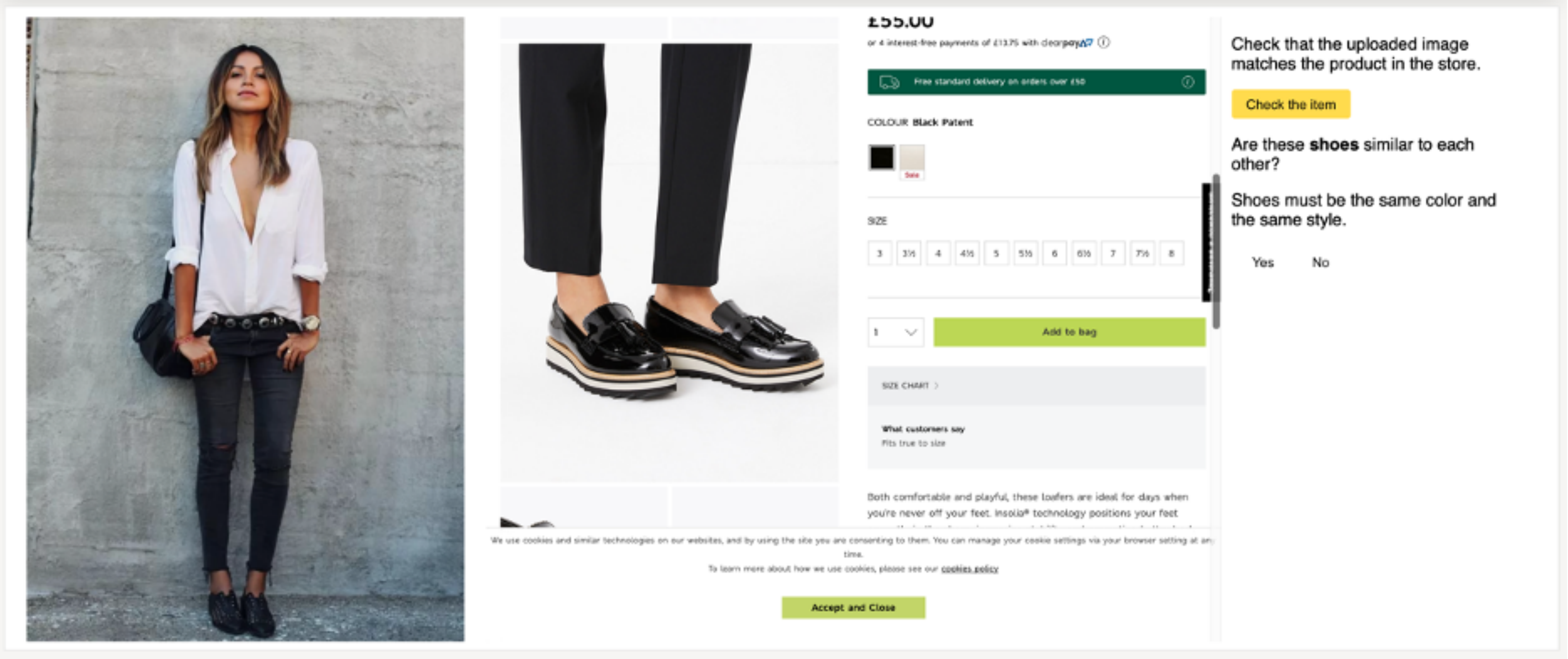
Project #3: Accept correctness of items found

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



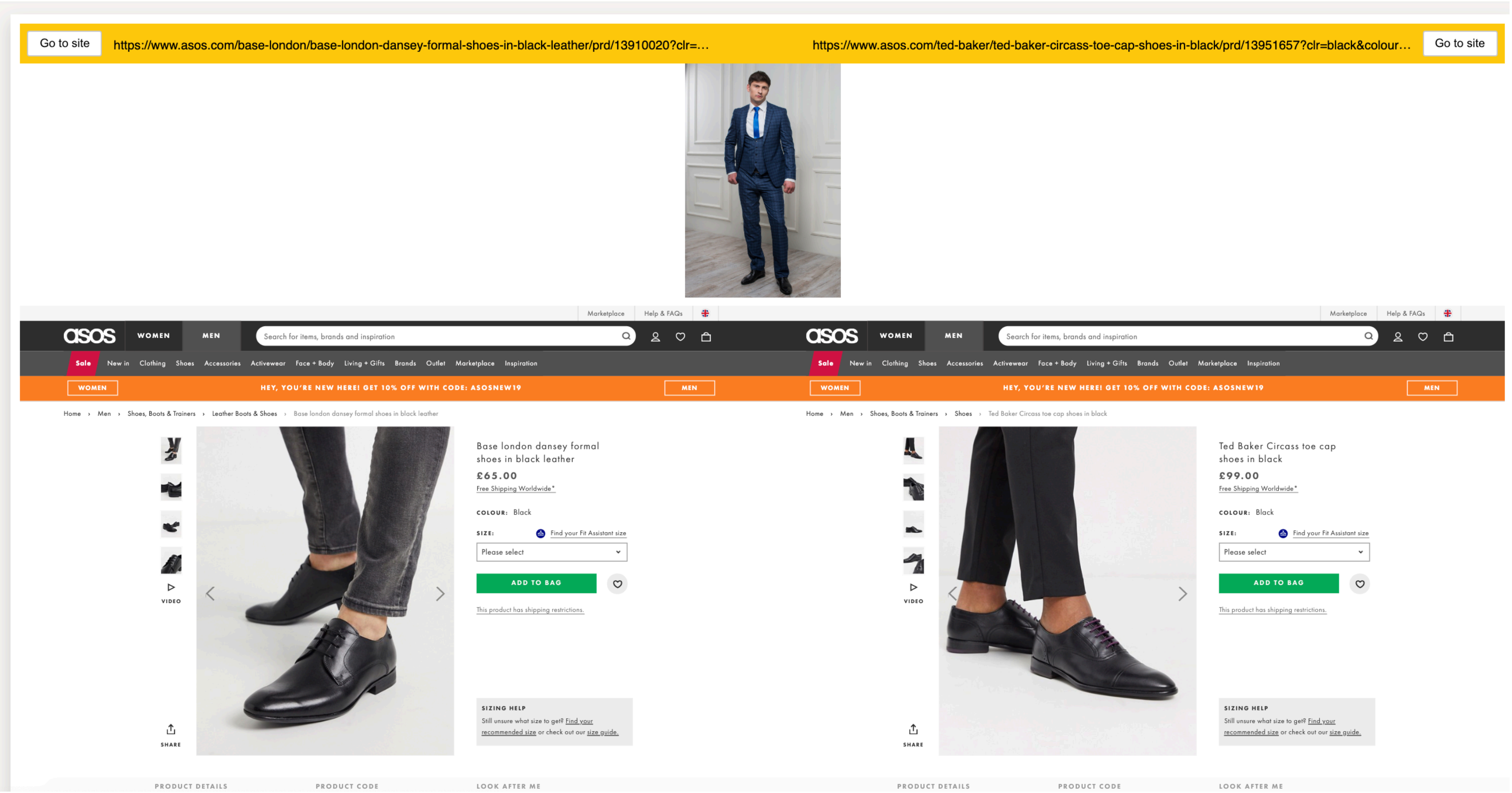
Project #4: Decide which substitute works best

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 Yandex.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

References: Aggregation

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Thank you!
Questions?

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https://research.yandex.com/tutorials/crowd/sigmod-2020