Google Landmark Challenge

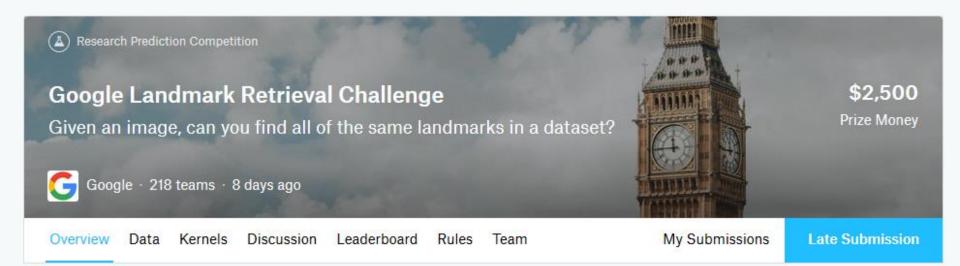
2018/7/19

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Overview

Description

Evaluation

Prizes

CVPR 2018

Timeline

Image retrieval is a fundamental problem in computer vision: given a query image, can you find similar images in a large database? This is especially important for query images containing landmarks, which accounts for a large portion of what people like to photograph.

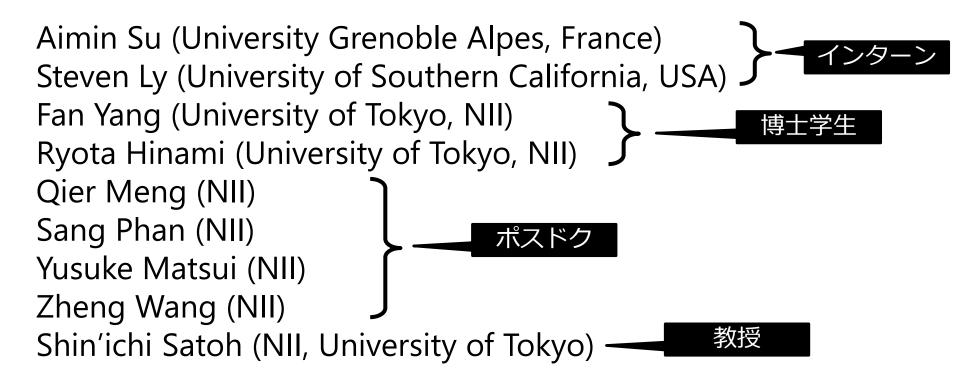
In this competition, Kagglers are given query images and, for each query, are expected to retrieve all database images containing the same landmarks (if any).

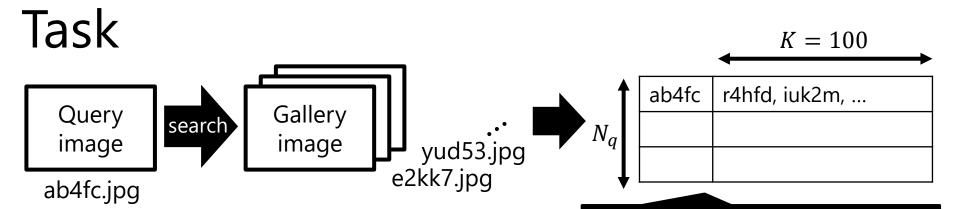
The new dataset is the largest worldwide dataset for image retrieval research, comprising more than a million images of 15K unique landmarks. We hope that this release will accelerate progress in this important research problem.

This challenge is organized in conjunction with the Landmark Recognition Challenge (https://www.kaggle.com/c/landmark-recognition-challenge). In particular, note that the test set for both challenges is the same, to encourage participants to compete in both. We also encourage participants to use the training data from the recognition challenge to train models which could be useful for the retrieval challenge. Note, however, that there are no landmarks in common between the training (index

NII佐藤真一研チームで参加

- > Retrieval task: **7**th place (in 209 teams)
- ➤ Recognition task: **7th** place (in 483 teams) どちらも日本からのチームのうち一位





- $N_q = 100K$
- $N_g = 1M$

- Report this
- Evaluated by mAP
- Groundtruth: same landmark

Query image ab4fc.jpg K = 100Search Gallery image N_q ab4fc r4hfd, iuk2m, ... N_q ab4fc r4hfd, iuk2m, ...

 $N_q = 100K$ $N_g = 1M$

- Report this
- Evaluated by mAP
- > Groundtruth: same landmark











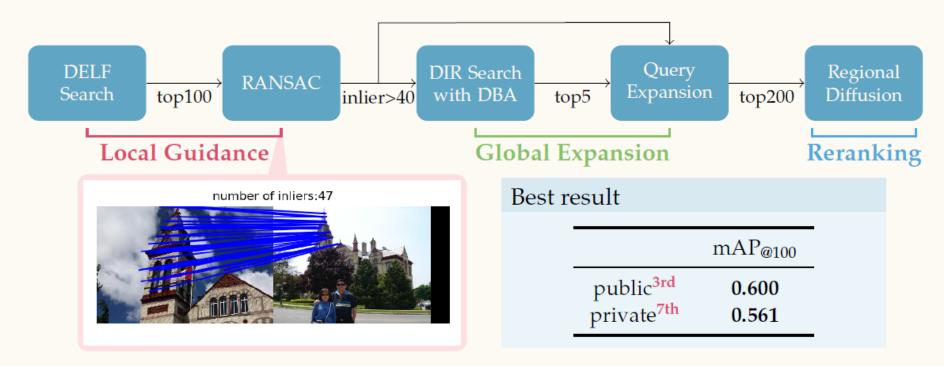




Query True

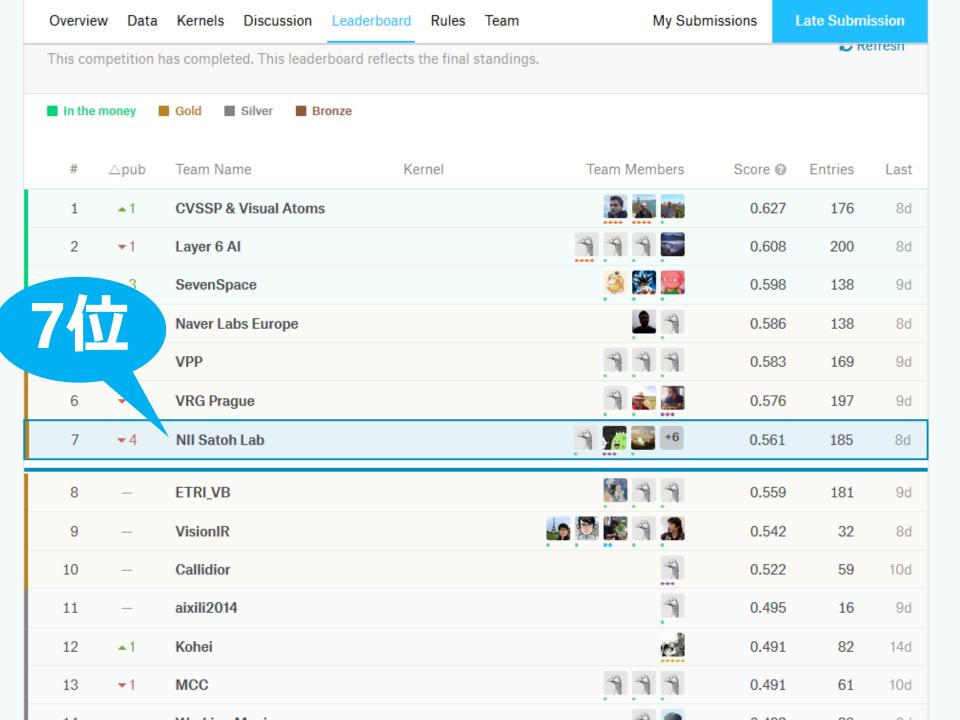
False

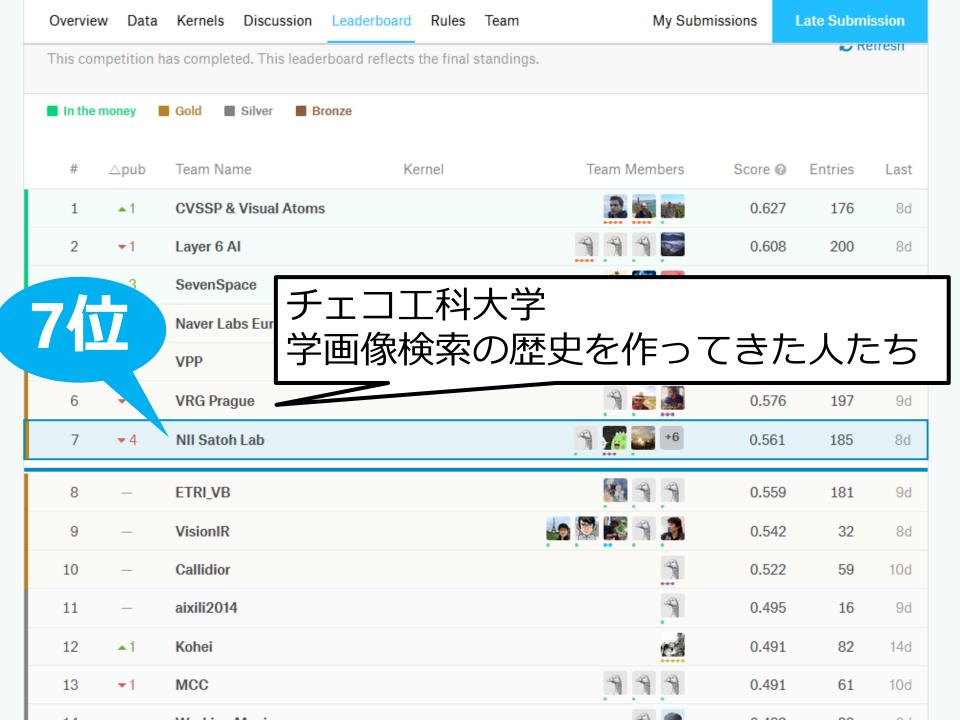
Landmark Retrieval via Local Guidance and Global Expansion

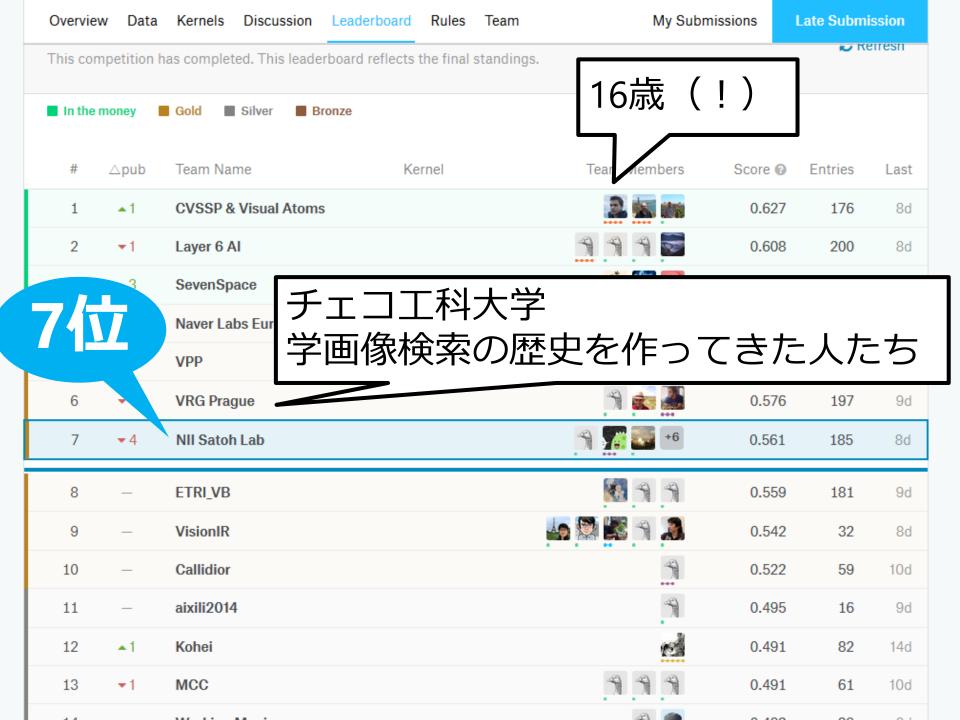


Main features:

- Spatial verification takes highly confident candidates;
- Global expansion allows better generalization;
- Regional diffusion reranks results on manifolds.

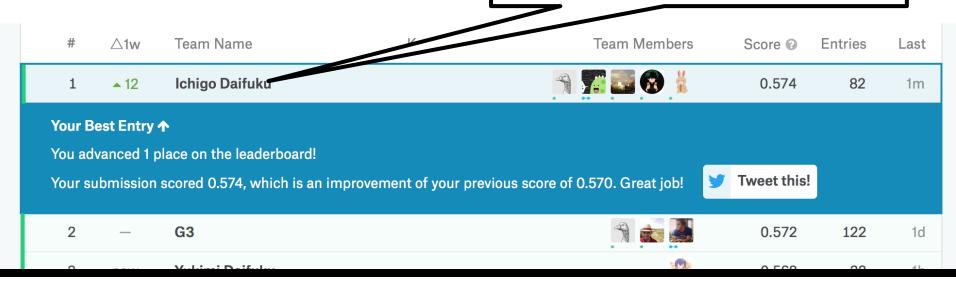


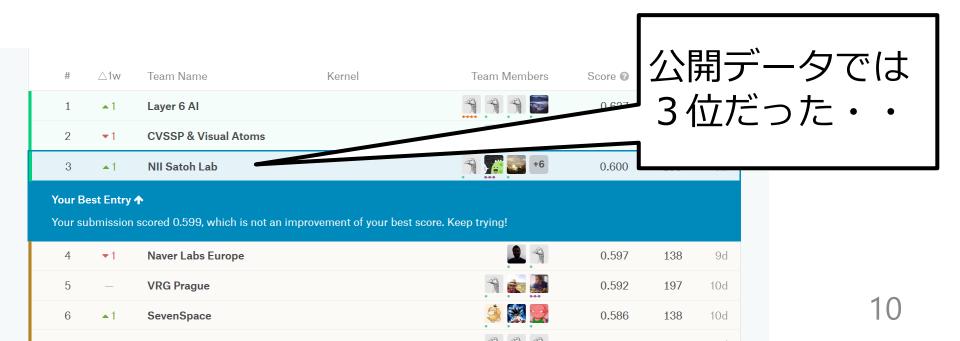




余談

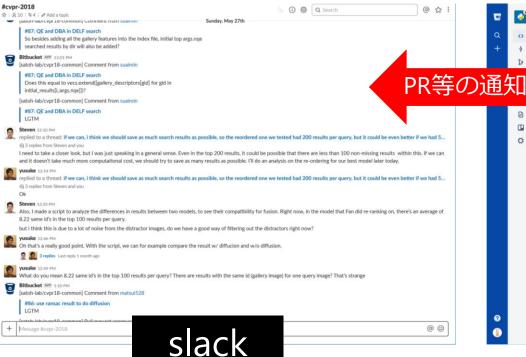
ー時期1位だった・・

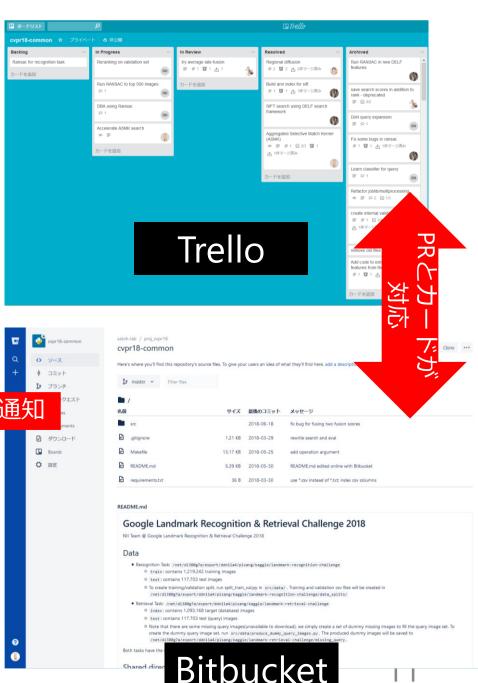




管理:

- ➤ Kanban (Trello) + Bitbucket + Slack でナウいチーム開発を目指した
- ➤ Github Flow
- ▶ なるべく処理をパイプライン化して分割することで、みんながコミットできるように
- (アカデミアにしては) 実装を頑張ったほうだと思われる





マシン:

ラボGPUサーバ:

- > V100 * 8, CPU 80 threads (DGX1)
- ➤ P100 * 4, CPU 28 threads
- ➤ K80 * 8, CPU 24 threads

ラボCPUサーバ:

➤ CPU 60 threads

AWS:

- ➤ x1e.32xlarge * 1 : vCPU 128, **3904** G mem, 26.7 USD/h CPU世代はHaswellで、これはdgx1のBroadwellより前
- ➤ m5.24xlarge * 10 : vCPU 96, 384G mem, 4.6 USD/h < 1.1万円/日 ご CPU世代は上より新しいSkylake
- ➤ EFSでファイル共有(各ec2インスタンスから共有マウント)



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学び

- ➤ マシン世代が違うとCUDAバージョン問題などに気を 使う必要がある
- ▶ DGX1はCPUもいいので、ついCPUもGPUも使うコード (e.g. faiss-gpu)を書いてしまいがちだが、後にAWS に移す可能性があるなら分けたほうがいい
- ➤ どうせ最後にAWSで気合ブーストするので、AWSに移 せるように意識してコードを書くといいと思う



3

マ<u>シン:</u>

ラオ学び:

- ► CPU世代が違うと速度がかなり違う。スレッド数だけで は決まらない
- ▶ K 巨大なマシン一台より、ミドルレベル複数台のほうがコスト的にも総メモリ的にも楽
- ラオ▶ EBSではEC2をポコポコ増やすときにデータ移動大変。 ▶♂ EFS推奨。ただEFSは書き込みが遅いときがあった

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6.4万円/日

MIRU 2018 (北海道)で発表します

CONFIDENTIAL EXTENDED ABSTRACT.
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The 21st Meeting on Image Recognition and Understanding

Landmark Retrieval via Local Guidance and Global Expansion

Aimin Su 1,2 Steven Ly 3,2 Fan Yang 4,2 Ryota Hinami 4,2 Qier Meng 2 Sang Phan 2 Yusuke Matsui 2 Zheng Wang 2 Shin'ichi Satoh 2,4

Abstract

Google recently held a competition on the Google-Landmarks dataset, the largest worldwide dataset of images for large-scale image retrieval research. We proposed our own model, which incorporated different modern image retrieval techniques together, and finished in 7th place in the competition. We present our full image retrieval model and its results, as well as go over the challenges we faced in the competition.

1. Introduction

With the explosive growth of multimedia data on the web, image retrieval is becoming a fundamental problem in computer vision. The task is straightforward: given a

3. Proposed pipeline

The pipeline of our image retrieval system is illustrated in Fig. 1. It consists of five key steps: (1) Deep local feature (DELF) search. (2) Sptatial verification (RANSAC) on top-100 results of (1). (3) Deep image retrieval (DIR) search with database-side feature augmentation (DBA). (4) Query expansion with top-5 results of (3) and the results of (2) with inlier > 40. (5) Re-ranking by regional diffusion. In the next sections, we go over the details of the different components of our pipeline, and also explain how they tie together.

3.1 Image Representation

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