Machine Learning and Vienna classification

Vienna Union/ Committee of Experts

02-02-2021

Christophe Mazenc

Director, Global Databases Division, Infrastructure and platforms Sector

Advanced Technology Application Center

WIPO
WORLD
INTELLECTUAL PROPERTY
ORGANIZATION

Outline

- Presentation of WIPO’s ATAC team
- WIPO’s Vienna classification assistant
- Brief presentation of the underlying technology
- Results
- Video demonstration
- Challenges and how to do better?
- Questions / Answers

ATAC Team

- **A**dvanced **T**echnology **A**pplication **C**enter
- Section within program 13 dedicated to the development of AI-based tools and applications for the benefit of WIPO:

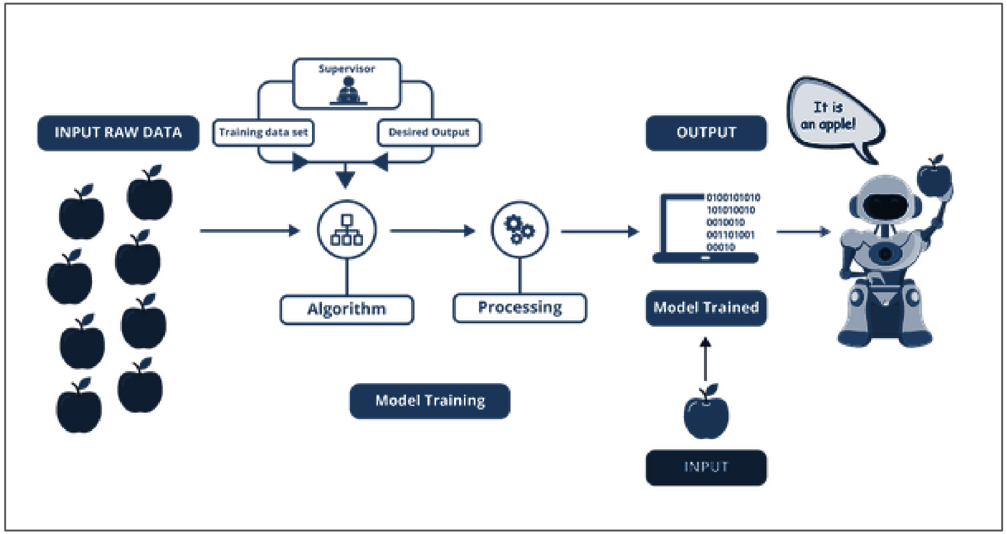
- Text processing
  - WIPO translate (Neural Machine Translation)
  - Text patent classification (IPC, CPC)

- Image processing
  - Global Brand Database Image Similarity Search
  - Vienna Classification Assistant
  - Global Designs Database

- Speech processing
  - WIPO Speech to Text
  - Speech to Translated Text

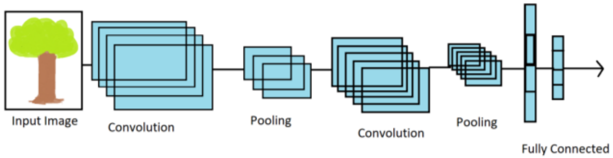
AI: Supervised machine learning

Supervised machine learning



3 essential ingredients for machine learning:

Big datasets



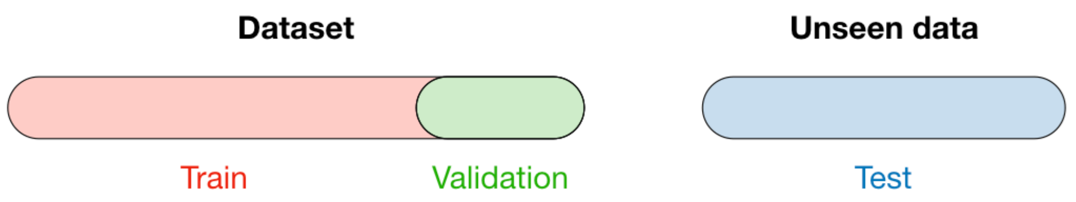
Neural Networks

Computing: Graphics Processing Units

Datasets

For Vienna v8 classification

- ~500k trademark (mostly non verbal) images from DE, DK, EE, EM, ES, FR GE, MX and WO collections
- Preprocessed: 224x224, centered cropped, 16-bits colors
- **Labelling** improved (outsourced work: 6 men-months)
- Manual **addition of images** for not/low-populated classes
  - To ensure there are at least 30 images per class
- 80% train, 10% validation, 10% test
- First version in production: classes under 28 not trained



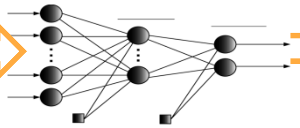
Results

Vienna v8 automatic classifier

- ~50 % top five accuracy
- ~40 % top three accuracy
- ~20 % top one accuracy

Image in test set

With the expected classification:
02.01.12 Sailors, seamen, fishermen, pirates



03.09.25 - Animals of division 3.9 in costume or personified

03.09.23 - Other aquatic animals

03.05.25 - Animals of Series V in costume or personified

03.05.17 - Other quadrupeds belonging to Series I to V

03.05.17 - Other quadrupeds belonging to Series I to V

03.05.19 - Monkeys, apes, orang-utans and other quadrumana

…

Results

Vienna v8 automatic classifier

- => Not reliable enough to get a reputable fully automated system
- Many reasons explain these results
- However, not as bad as it looks: when you look at examples, in the first 32 classes ranked first by neural network, many are relevant
- We also observed that if you filter the results returned by the neural network by selecting the appropriate first level(s) of the Vienna classification, the detailed classifications obtained are a lot more accurate

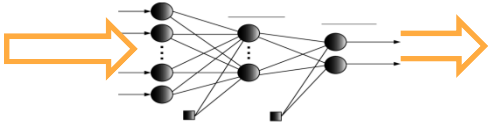
Results

Filter with 02 - HUMAN BEINGS

Helping the neural network with first level filtering

Image in test set

With the expected classification:
02.01.12 Sailors, seamen, fishermen, pirates



02.01.07 - Harlequins, clowns, pierrots, carnival characters or grotesque or freakish figures, dwarfs, wizards;

02.01.01 - Heads, busts (men);

02.01.12 - Sailors, seamen, fishermen, pirates;

02.09.12 - Hair, locks of hair, wigs, beards, moustaches;

02.01.19 - Men smoking;

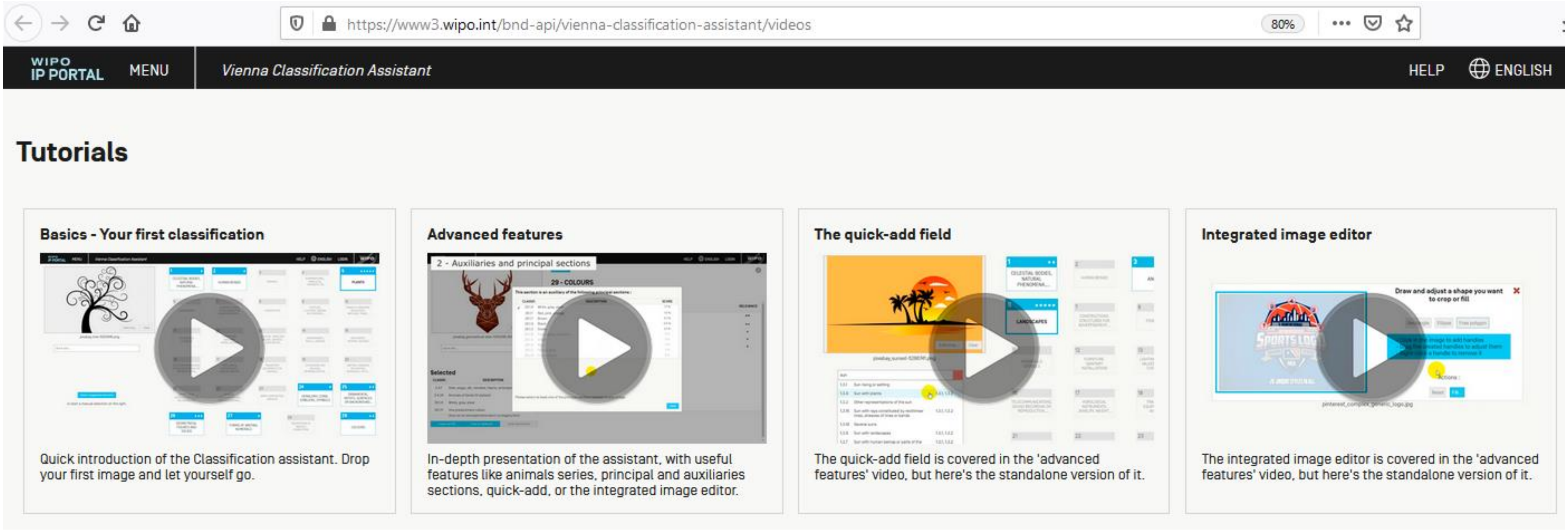
02.01.15 - Other professionals (men);

02.01.04 - Men wearing folk or historical costume

...

Vienna classification assistant

Freely available on the internet at: https://www3.wipo.int/bnd-api/vienna-classification-assistant/



Challenges

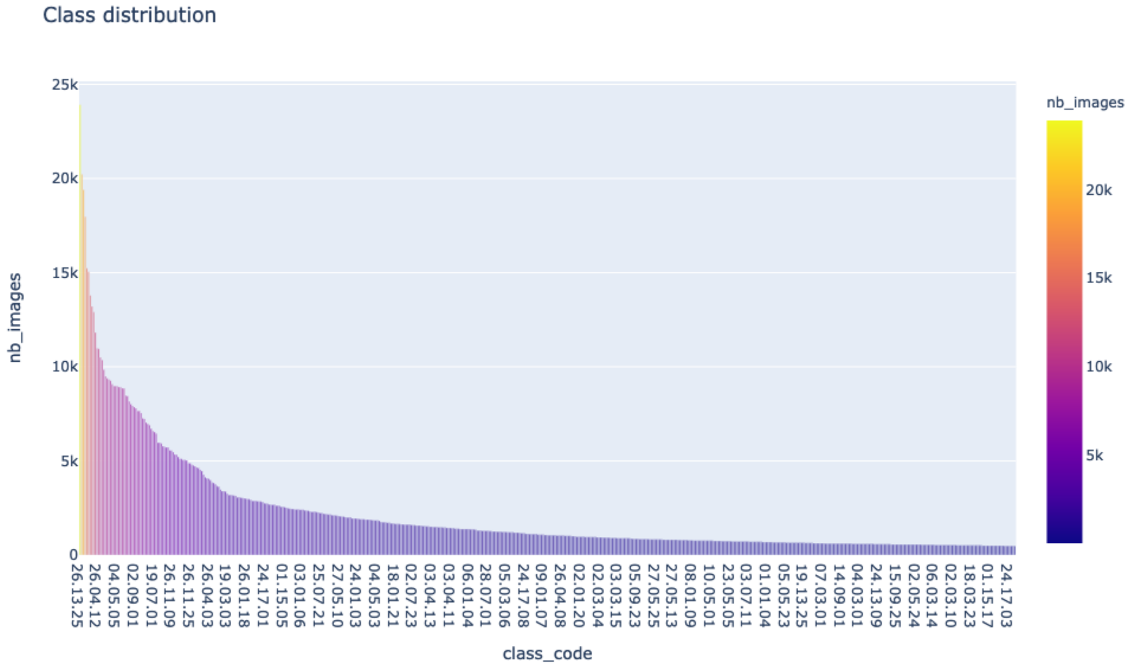
Challenge 1

Unbalance of Training set

❖ Some classes are over-represented (>5000 examples), some others are under-represented (less than 10)

❖ After a lot of efforts to “complete” the under-represented classes:

~400 classes with less than 200 images
~100 classes with less than 100 images



Challenge 2

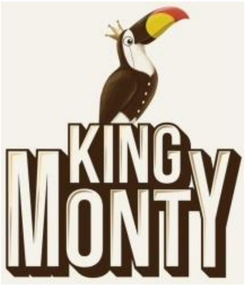
Issues in quality in training set

- ❖ A non negligible share of the Vienna classifications that we have access to in the Global Brand Database are wrong or outdated (after successive revisions of the classification)

- ❖ Classified images may miss an important classification (human error), which leads to «learning» a counter example

- ❖ Classifications are attributed without recording the level of relevance of each code for the image: impossible to know if a classification is important for an image or anecdoctical. E.g. when a trademark displays a pair of glasses, the corresponding classification may be attributed to it, even if the pair of glasses takes less than 5% of the non background part of the image:







=> Garbage in / garbage out principle: this pollutes the quality of the achievable results

Challenge 3

Training set too small
Ideally, we would need 500 good examples per classification to train with good conditions

⇒ Not possible with one national trademark collection for Vienna

⇒ Merging national collections brings confusion problems:

Classification practices differ significantly between countries due to:

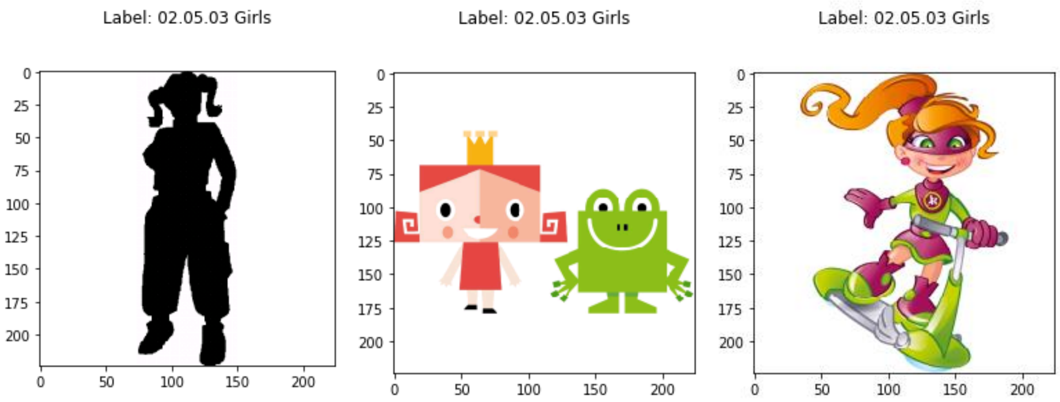
- Different interpretations of classes definitions due to different cultural background / speaking language
- Different ways of learning how to classify
- Classification methods differ, notably in terms of number of classifications to assign, what to classify in images…
- An image is inherently subjective, and different classifiers, even from the same office will not classify images in the same way

Challenge 4

Some class definitions are too wide, leading to the non-existence of common visual patterns suitable to be automatically selected by a convolutional neural network (the images within the same class look too dissimilar).

This is the case for many of the «other» classes xx.yy.25

Even unambiguously defined classes like «**02.05.03 – girls»** exhibit large graphical variation:



Can a non expert guess which class is it?

Any visual caracteristic in common?

Food for thought from the viewpoint of the use of Artificial Intelligence

- ❖ When modifying/adding a class in the future, provide 30 representative best distinct examples (if possible 50)
- ❖ Consider to delete classes where less than 50 good representative trademarks are available worldwide
- ❖ Possibility to add an attribute: principal or secondary when attributing a classification to an image (Only principal classifications would be used for training sets)
- ❖ Consider the use of WIPO's classification assistant to align practices between offices (for classifying and/or training new classifiers)
- ❖ Consider to split classes where the definition is too wide (notably «other» classes). Automatic classification tools can probably be trained to recognize 2500 classes and humans can be assisted by tools to compensate the increase in number of classes
- ❖ Define classes having in mind they exhibit common visual patterns (if a human cannot guess the class, a machine will also have difficulties in classifying it)
- ❖ Please do not hesitate to provide us with feedback about what you like/don’t like about the Vienna Classification Assistant so that we can improve it in the future
- ❖ Ask applicants to furnish high resolution images for logos (ideally 512x512)

Questions / Answers

- For next years, would an AI-based reclassification tool assisting to reclassify the trademarks that belong to reclassified categories be a project of interest?