The MET Dataset

Instance-Level Recognition Workshop
ICCV' 21

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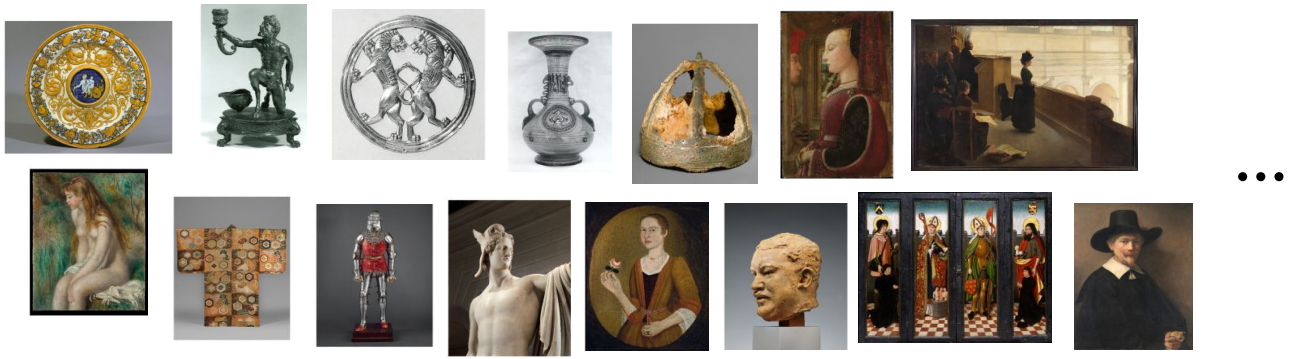
Artwork recognition dataset - motivation

- Real-world applications of artwork recognition
- New domain compared to existing instance-level recognition (ILR) datasets
- Challenging for existing methods

Artwork recognition



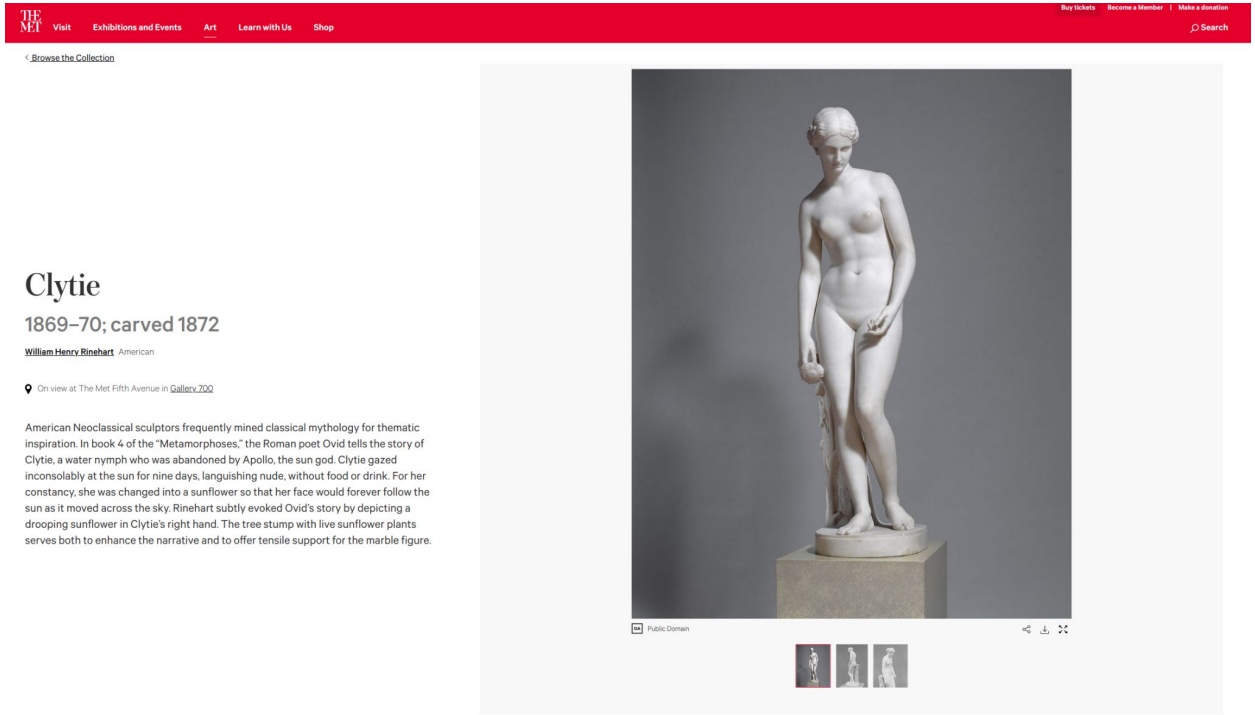
Training set

Query / test

Artwork Classifier

Artwork: California, Hiram Powers, 1850–55
Confidence: 92 %

Metropolitan Museum of New York (MET) - training set

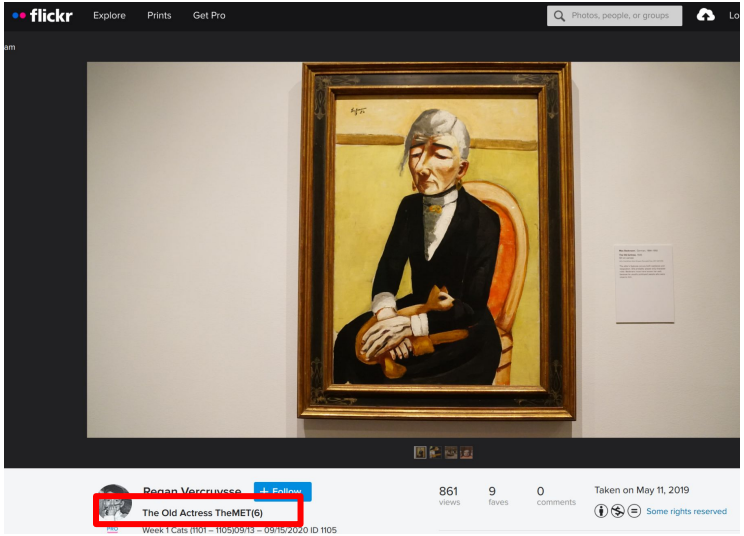


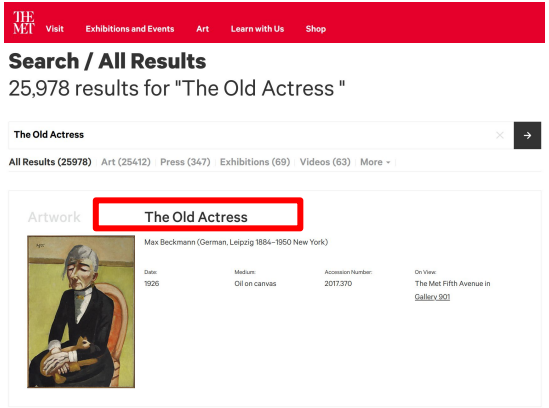
- **Public domain** images (CC0) from The MET open collection
  - Studio conditions
  - Multiple views
- Collection
  - Download all images
  - Automatic deduplication
  - Max 10 images/artwork
  - No extreme aspect ratios
  - Down-sample
- Total
  - ~397k images
  - ~224k artworks (classes)

Queries from The MET

Flickr photos

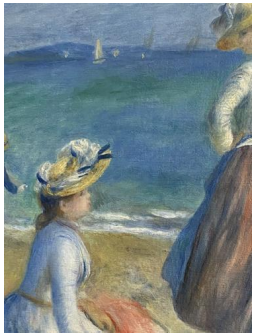
- Crawl MET related photos
- Creative Commons license
- Photos by 38 MET visitors
- Annotation:
  - Text matching
  - Manual filtering





Own photos (Guangxing)

- Faster annotation



Distractor queries

- Follows the paradigm of GLDv2
- Real-world setting:
  - Photos not from “The MET”
- Test robustness to Out of Distribution (OoD) input
- Use Wikimedia commons Public Domain images

Artwork **distractors**

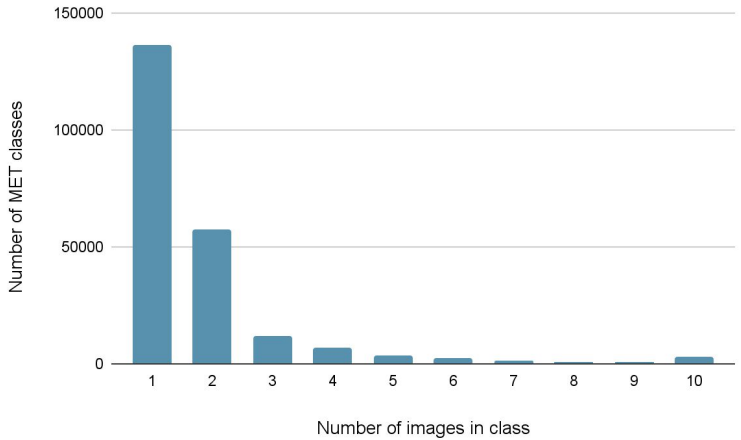
- manual verification

Non - Artwork **distractors**

Dataset statistics - challenges

- Exhibits (train set)
  - 397k images
  - 224k classes
- Queries
  - 21k images
    - 1,1k MET queries
      - 845 classes
      - 14 departments (balanced)
    - 20k distractors
      - Art : 11k
      - No-art : 9k

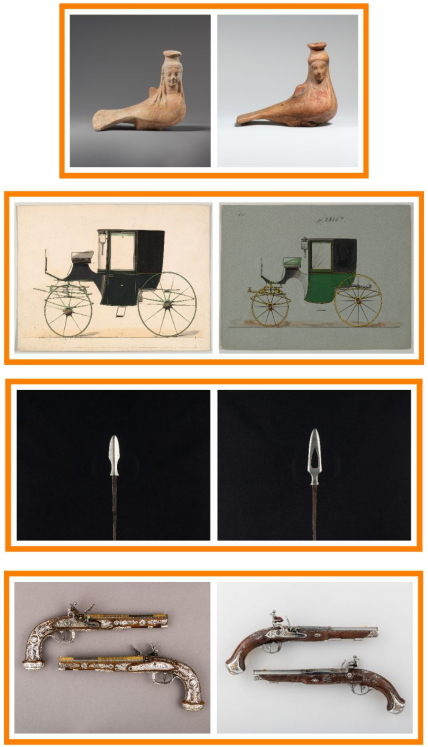
- Large-scale recognition
- Long-tail distribution

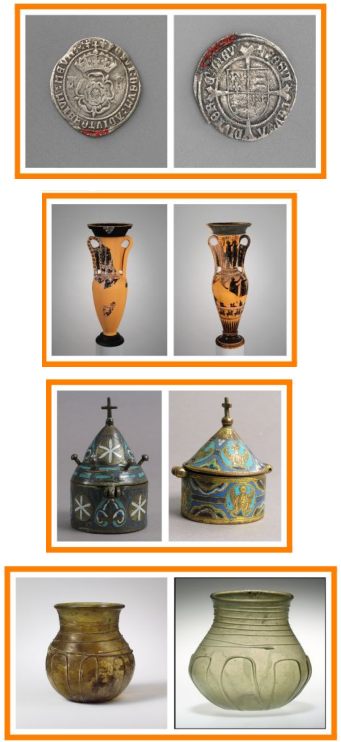


- Distractor (OoD) queries
- High inter-class similarity
- Domain shift between exhibits and queries

High inter-class similarity

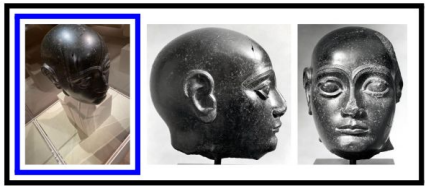
- Examples of visually similar classes





Domain shift

- Viewpoint and illumination changes
- Clutter



Comparison to other datasets

Current Art datasets :

- Attribute prediction
- Category level recognition
- ILR ones:
  - Smaller and noisy

Art datasets	Year	Domain	# Images	# Classes	Type of annotations	Task	Image source
PrintArt [5]	2012	Prints	988	75	Art theme	CLR	Artstor
VGG Paintings [10]	2014	Paintings	8,629	10	Object category	CLR	Art UK
WikiPaintings [20]	2014	Paintings	85,000	25	Style	AP	WikiArt
Rijksmuseum [27]	2014	Artwork	112,039	†6,629	Art attributes	AP	Rijksmuseum
BAM [39]	2017	Digital art	65M	†9	Media, content, emotion	AP, CLR	Enhance
Art500k [26]	2017	Artwork	554,198	†1,000	Art attributes	AP	*Various*
SemArt [14]	2018	Paintings	21,383	21,383	Art attributes, descriptions	Text-image	Web Gallery of Art
OmniArt [35]	2018	Artwork	1,348,017	†100,433	Art attributes	AP	*Various*
Open MIC [22]	2018	Artwork	16,156	866	Instance	ILR (DA)	*Authors*
iMET [41]	2019	Artwork	155,531	1,103	Concepts	CLR	The MET
NoisyArt [11]	2019	Artwork	89,095	3,120	Instance (noisy)	ILR	*Various*
The MET (Ours)	2021	Artwork	418,605	224,408	Instance	ILR	*Various*

Comparison to other datasets

Current ILR datasets :

- Not art
- Large but noisy
- Not fully publicly available

ILR datasets	Year	Domain	# Images	# Classes	Type of annotations	Image source
Street2Shop [17]	2015	Clothes	425,040	204,795	Category, instance	*Various*
DeepFashion [25]	2016	Clothes	800, 000	33,881	Attributes, landmarks, instance	*Various*
GLD v2 [38]	2019	Landmarks	4.98M	200,000	Instance (noisy)	Wikimedia
AliProducts [8]	2020	Products	3M	50,030	Instance (noisy)	Alibaba
Products-10K [2]	2020	Products	150,000	10,000	Category, instance	JD.com
The MET (Ours)	2021	Artwork	418,605	224,408	Instance	*Various*

Benchmark

- Training set: MET open collection images
- Queries are split into test and val sets
  - 90 - 10 % image splits
  - No overlap of photographers or classes
- Test
  - 1,003 MET
    - 25 photographers
  - 18,316 distractors
- Val
  - 129 MET
    - 14 photographers
  - 2,036 distractors
  - Hyperparameter tuning

Evaluation metrics: accuracy and GAP





Accuracy = 66.6%

Sort





Global Average Precision =
⅓ * (1+0.5) = 0.5

confidence:	0.99	0.95	0.85	0.60	0.45
precision:	1	0.5	0.33	0.5	0.4
correct:	1	0	0	1	0





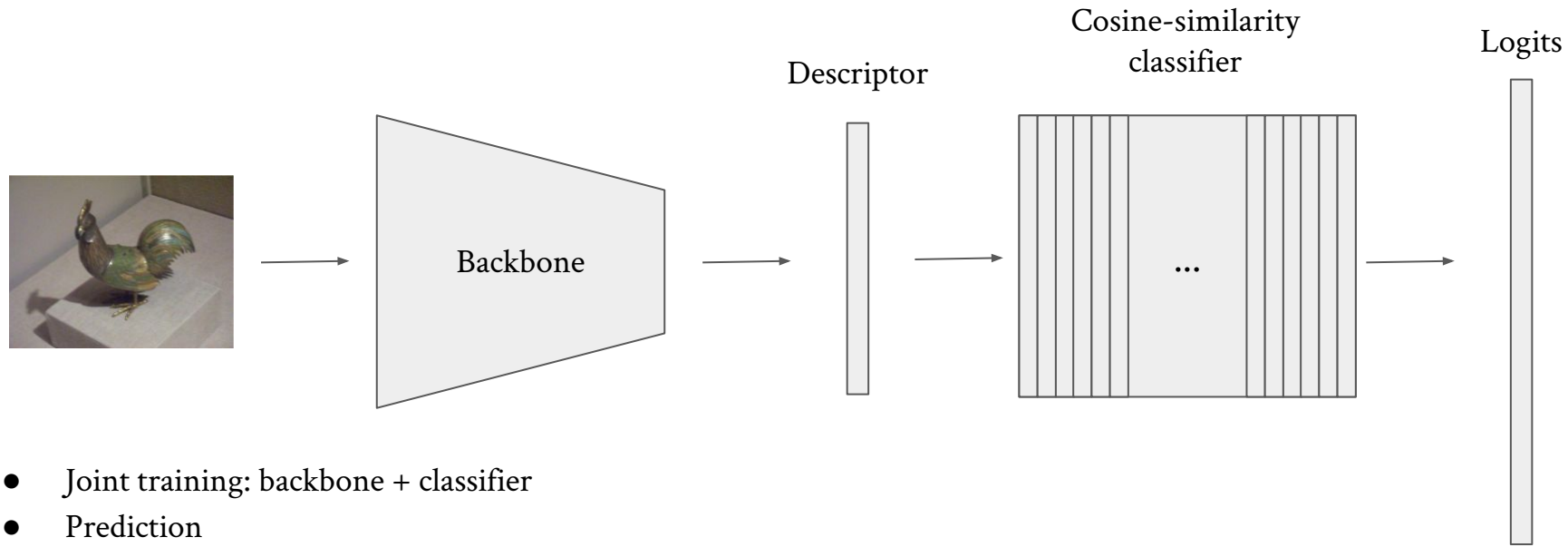
Global Average Precision = 0.81





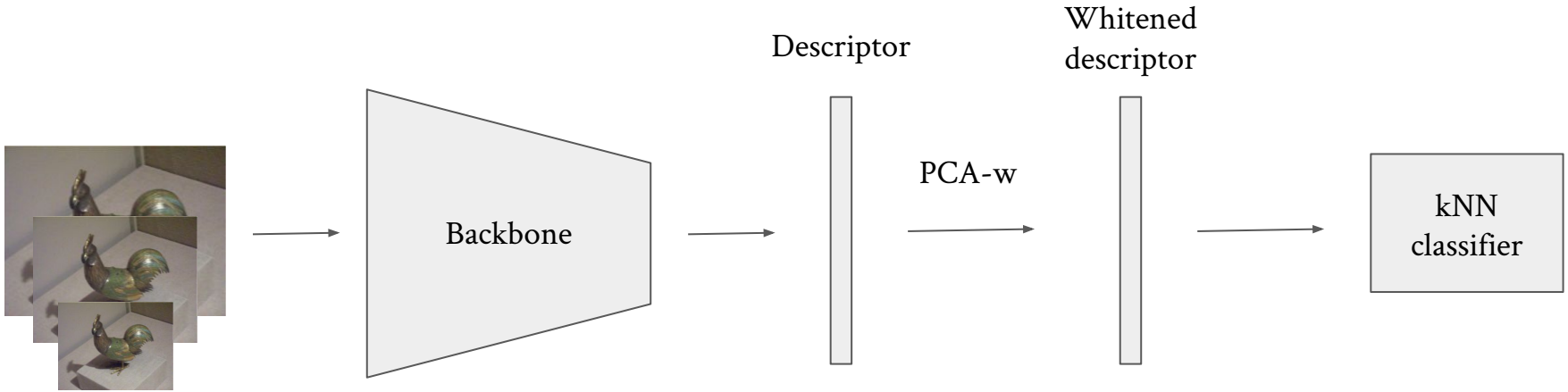
Global Average Precision = 1

Baselines : parametric classification



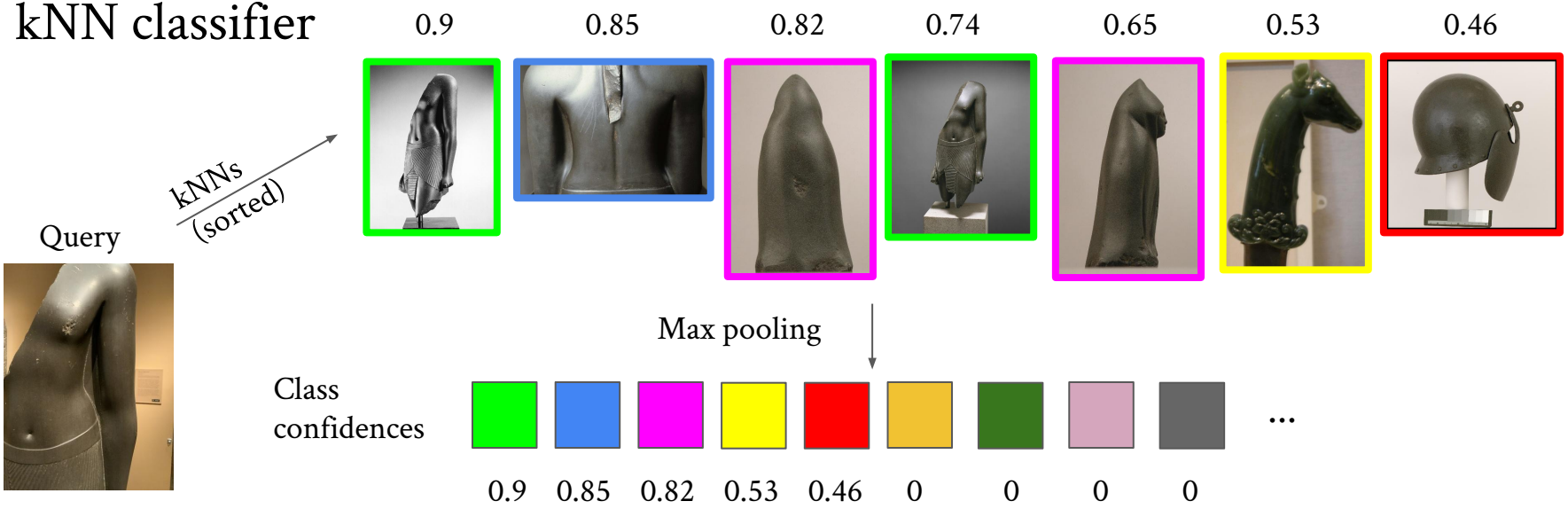
- Joint training: backbone + classifier
- Prediction
  - Argmax
- Prediction confidence
  - Softmax with temperature (τ)

Baselines : non-parametric classification



- Backbone: pre-trained or fine-tuned on MET
- PCA-whitening
  - Learned on train set
- Multiscale representation
  - By sum-aggregation

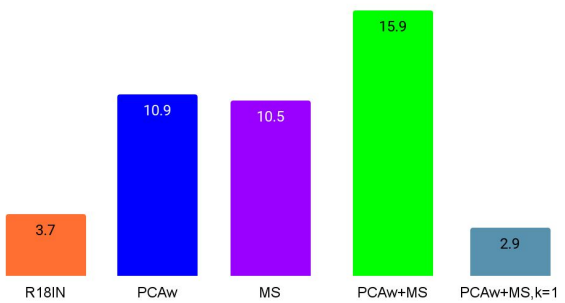
kNN classifier



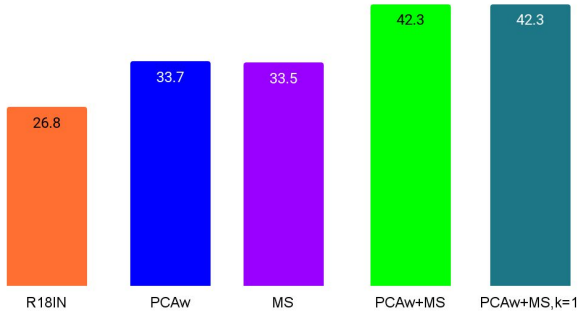
- Prediction
  - First neighbor
- Prediction confidence
  - Normalization by softmax with temperature (τ)
  - Affects GAP, not accuracy
- Number of neighbors (k) and temperature (τ) tuned on val set

Performance evaluation: kNN classifier

GAP



ACC



R18IN:
pre-trained
on ImageNet

no (k,τ) tuning

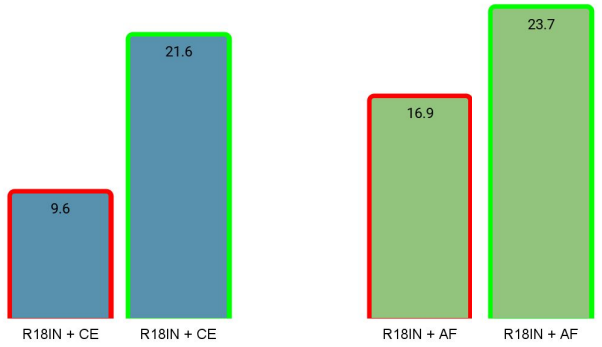
Different pretrained models: kNN classifier

		GAP	ACC
He et al. : Deep residual learning for image recognition.	R50IN	22.2	46.4
Radenović et al. : Fine-tuning cnn image retrieval with no human annotation.	R50SfM	26.6	48.6
Garcia et al. : Context-aware embeddings for automatic art analysis.	R50SemArt (author)	1.8	18.0
	R50SemArt (type)	7.9	31.9
Geirhos et al. : Imagenet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness.	R50SIN	15.5	41.7
Caron et al. : Unsupervised learning of visual features by contrasting cluster assignments.	R50SwAV	22.8	49.6
Yalniz et al. : Billion-scale semi-supervised learning for image classification.	R50SWSL	**30.4**	**56.3**

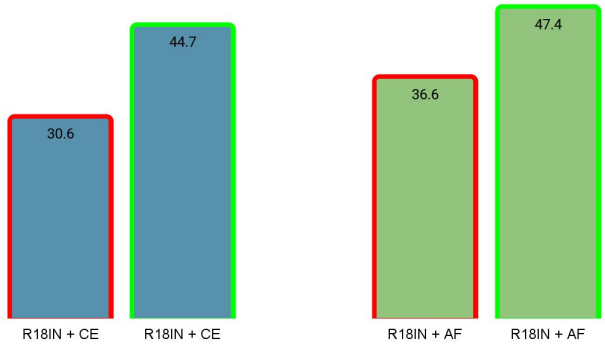
Parametric vs non-parametric classifier

- classification training (parametric)
  - Cross-Entropy
  - Arc-face [Deng et al.]
- use embedding for kNN classification (non parametric)

GAP



ACC



[Deng et al. : Arcface: Additive angular margin loss for deep face recognition]

Representation learning on MET

- SimSiam [Chen et al.]
  - Synthetic positives only

SimSiam method

- Contrastive
  - Hard-negative mining

hard negative

anchor

positive

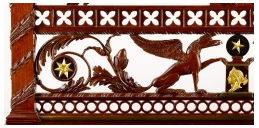
Contrastive loss

candidate positives

case 1 (Con1)

case 3 (Con3)

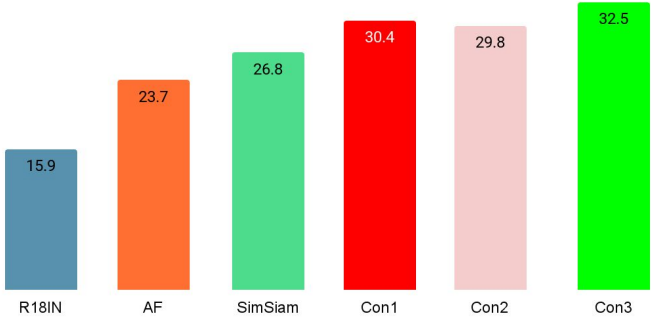
case 2 (Con2)



[Chen et al. : Exploring simple siamese representation learning]

Performance evaluation: representation learning on MET - kNN classifier

GAP

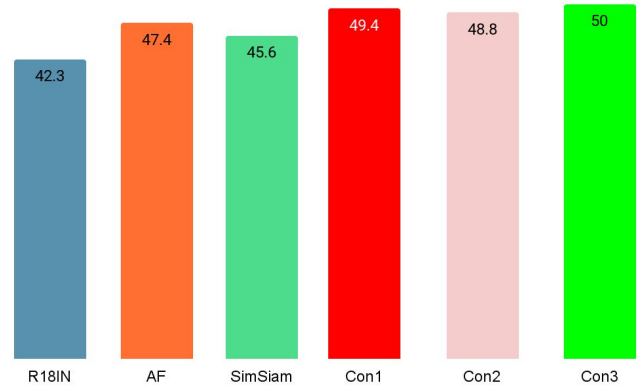


synthetic positives

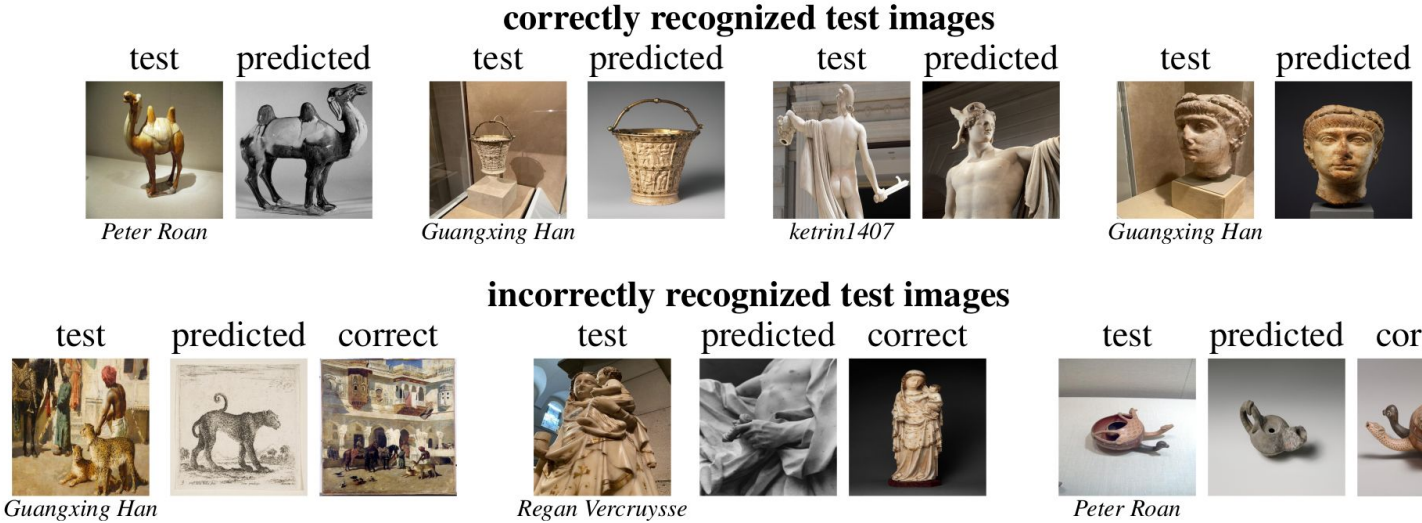
synthetic + real positives

synthetic + mined real positives

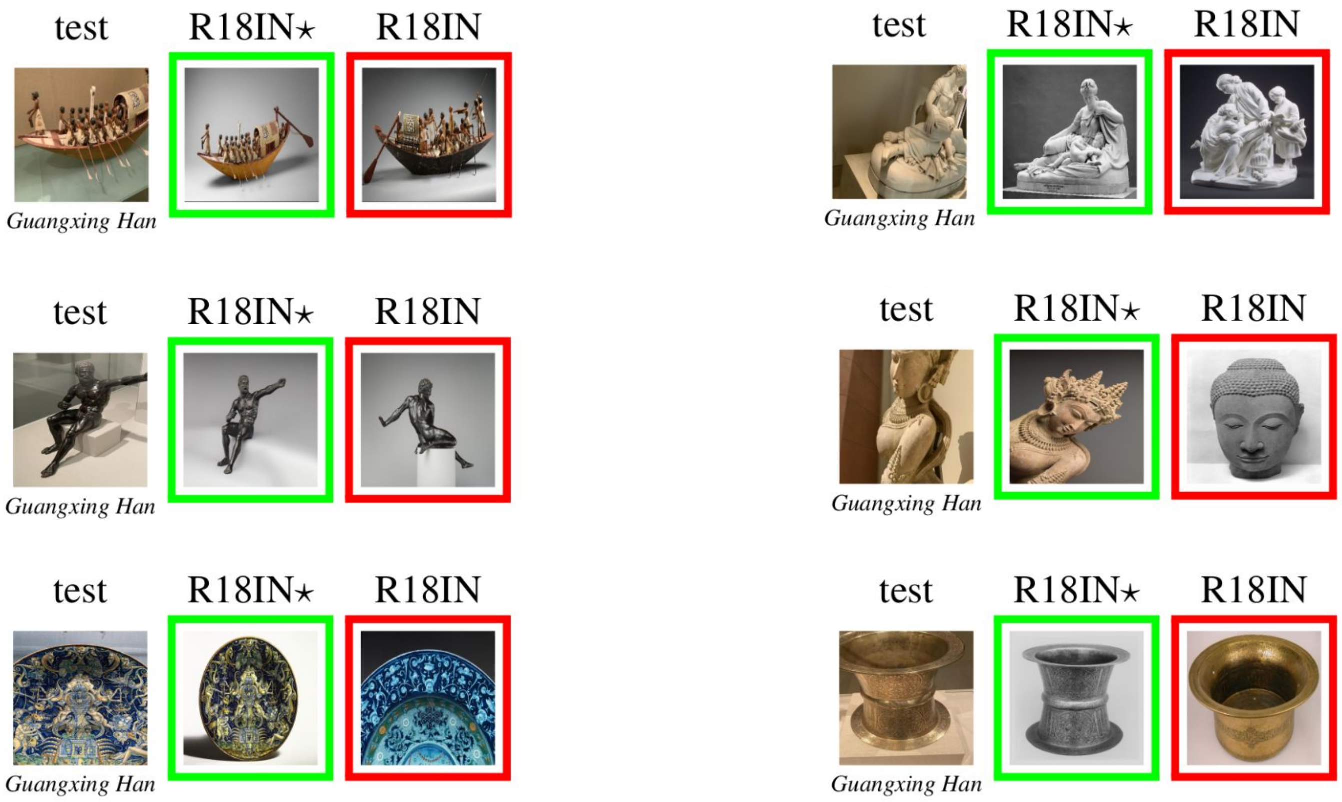
ACC



Qualitative examples



Pre-trained model (R18IN) vs training on MET (R18IN★)



Conclusions

- New dataset on large-scale ILR of artworks
- Complements existing ILR datasets
    - Support future research: generic ILR methods applicable to many domains

- Artwork related pre-training is not necessary useful
    - ILR-related pre-training is more relevant

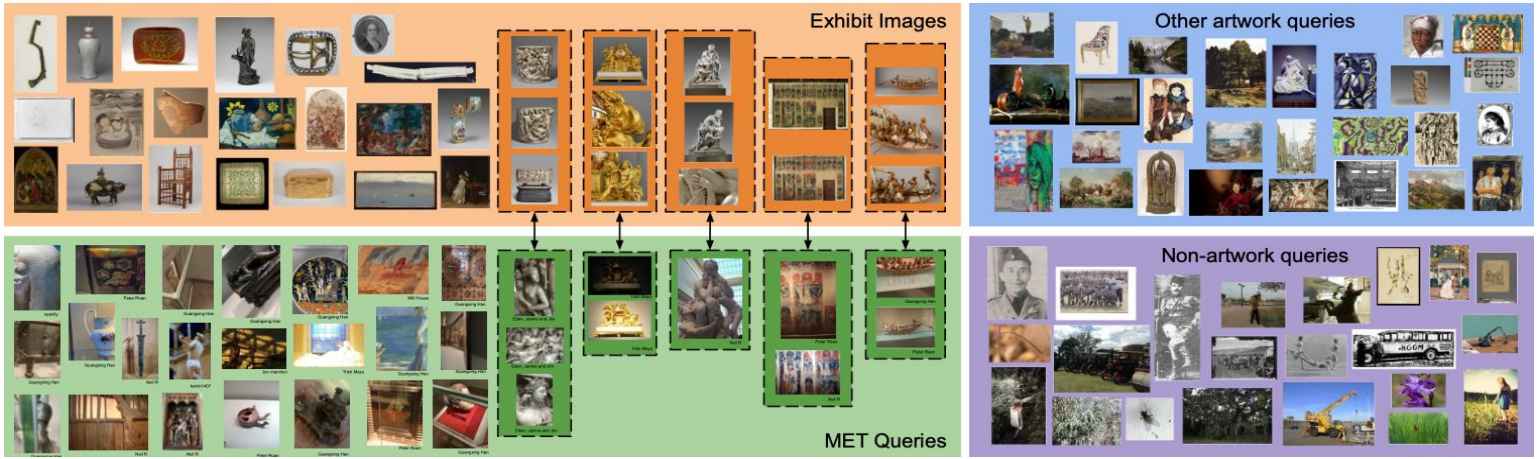
- Superiority of non-parametric vs parametric classifier
- Learning on the MET training set is challenging
    - Relevance of self-supervised representation learning

Dataset page: http://cmp.felk.cvut.cz/met/

Code: https://github.com/nikosips/met

Paper: "**Instance-level Recognition for Artworks: The MET Dataset**"

NeurIPS'21 - Datasets and Benchmarks Track



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