**Motivation**
- CNNs on a specific set of annotated classes → More generic and compact features for novel-category, small-sample recognition
- Unsupervised hyper-training over pre-trained, supervised CNNs
- A novel angle in using binary codes to achieve compactness
- Conventional specific binary codes → A large library of universal binary codes informative for novel concepts
- Unsupervised code generation
- Task-specific code selection

**Pipeline**
- Labeled images → Code design → Testing phase
- Unsupervised hyper-training phase (in a CNN feature space)
- In Parallel

**Qualitative Visualizations**
- Pseudo-class visualization (random)
- Attributes discovery and visualization (hand-picked)

**Unsupervised Hyper-Training**
- Feature Space: Pre-trained Alexnet CNN on ILSVRC 2012
- Unlabeled Data Corpus: 2M random subset of Yahoo/Flickr 100-million
- UPBC: Unsupervised discovery of Predictable Discriminative Binary Codes (PBCs) (Rastegari et al.)
- A novel angle in using Q in CNN Feature Space
- Training Phase
- Compact
- Diversified Pseudo-Labeled Data Generation
- Learning UPBCs
- Calibration
- Code Length

**Comparisons with SOA Binary Codes**
- UPBC Library: 20,000 binary codes
- Target Tasks: Multi-class recognition on Caltech-256
- Evaluation: Influence of training set size & code length
- Baselines: Classifiers-like approaches & binary codes over CNNs

**Generalization to Scene Classification**
- Target Tasks: Large-scale scene classification on SUN-397 & MIT-67
- Evaluation: Informative across categories/tasks & Comparison with CNN fine-tuning

**Conclusions**
- A large collection of universal and expressive binary codes that encode the visual space in an unsupervised, unbiased manner
- A far smaller set of annotated samples
- An efficient way to generate new models in terms of computation and storage
- A promising framework of leveraging both pre-trained features (CNNs) and pre-trained classifiers (on unlabeled data)