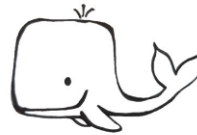


LLC: Accurate, Multi-purpose Learnt Low-dimensional Binary Codes

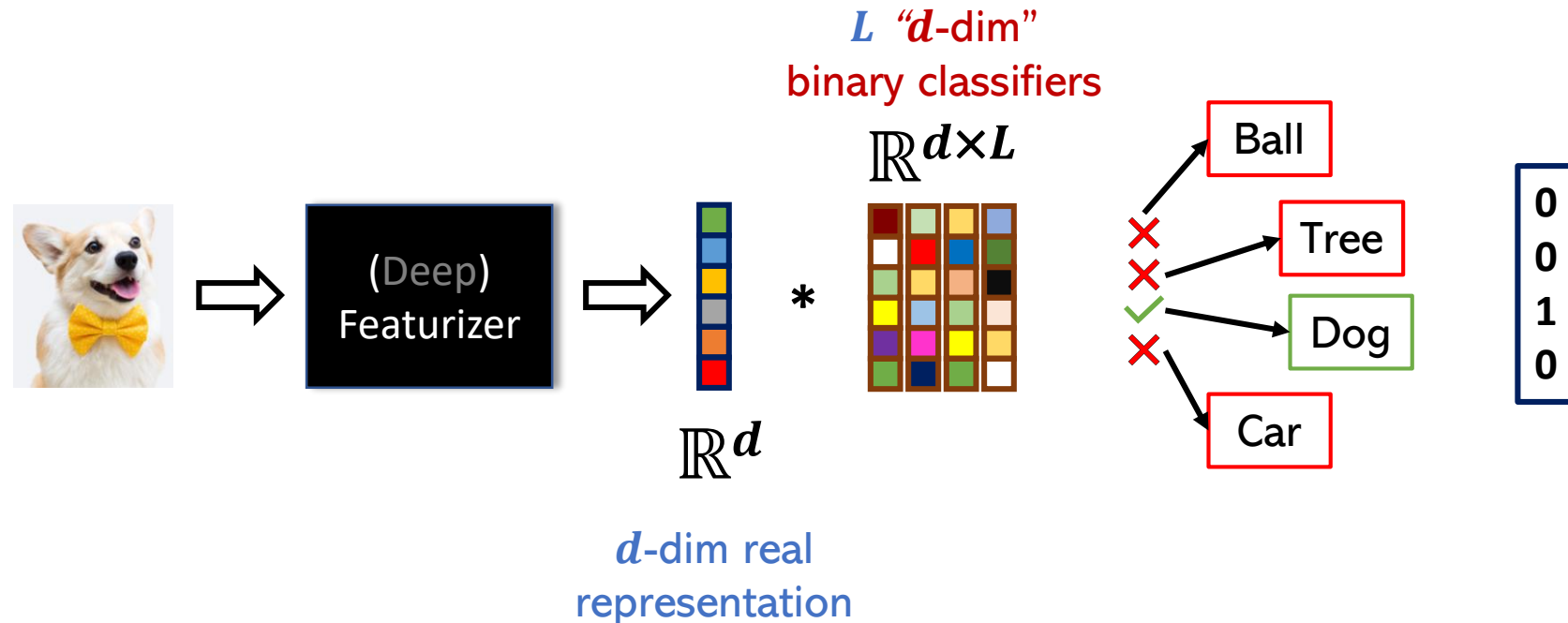


Aditya Kusupati



Multiclass Classification

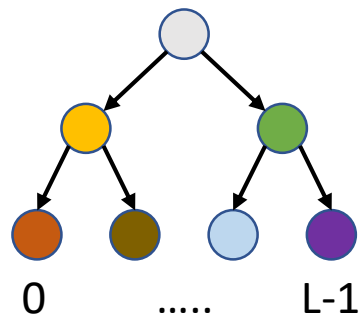
- Answers an MCQ among L options (classes / labels)
- (Typically) solved using L binary classifiers w/ only **one correct** answer
- Total probability of all classes sums to **1**



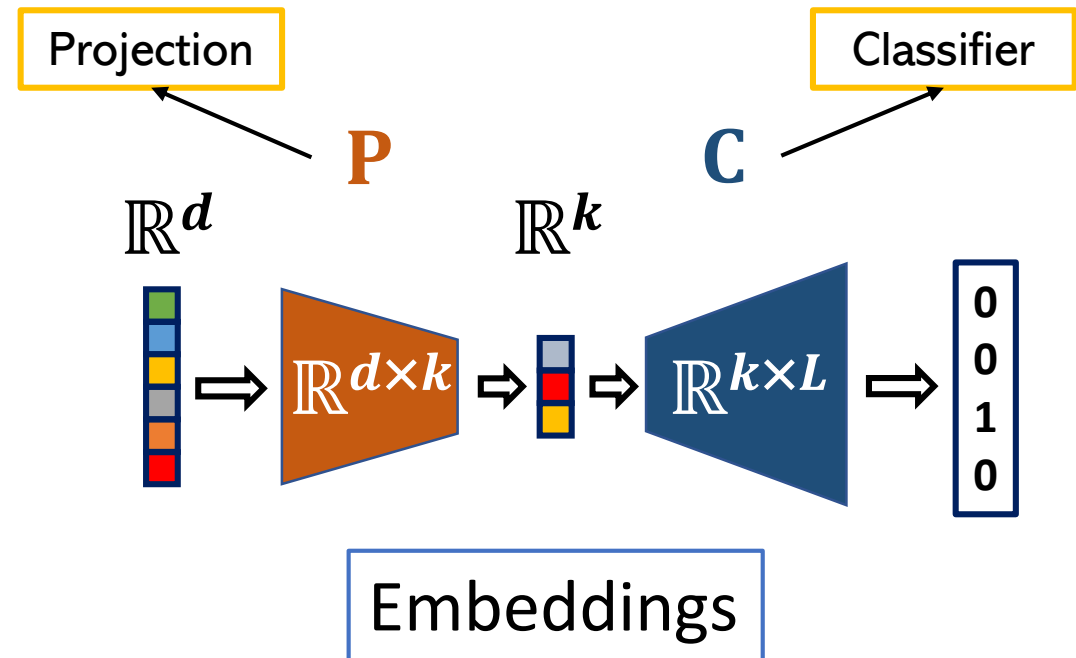
Multiclass Classification: Costs & Trade-offs

- Constant featurization costs
- Linear Classifier: $\mathbb{R}^{d \times L}$ – compute & memory scale as $O(d * L)$

Alternatives:

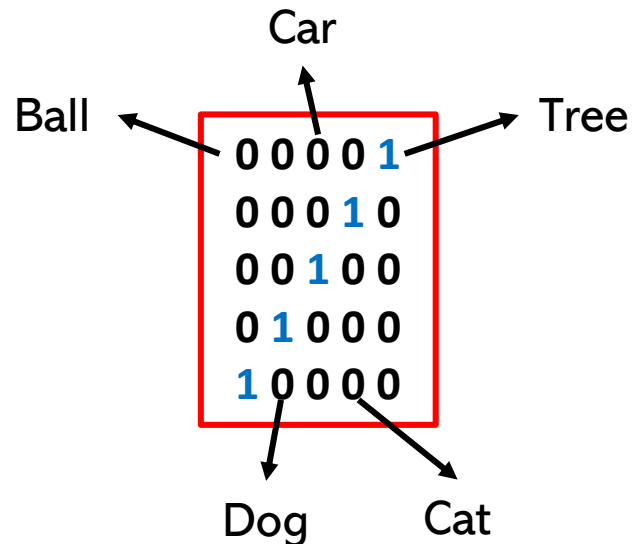


Trees / ANNS



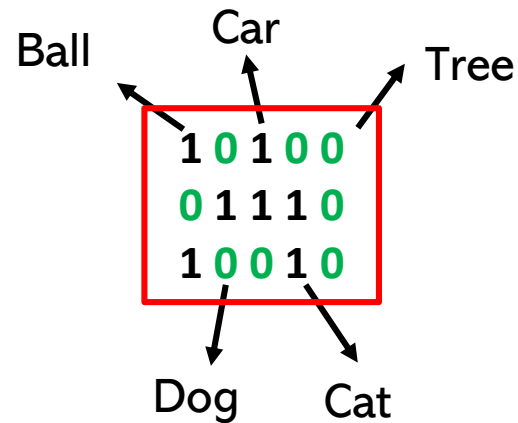
Multiclass Classification: Output Codes

- Typically, one-hot vector per class
- Very sparse; can we do better?



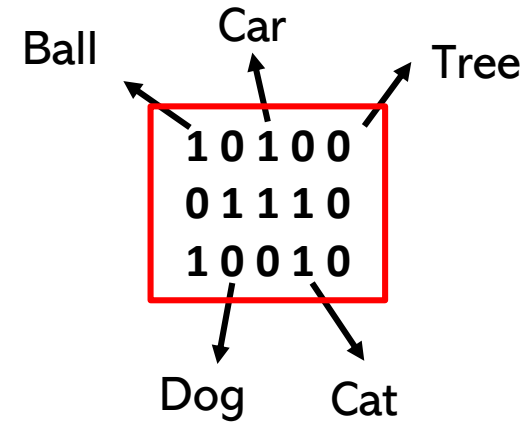
Multiclass Classification: Output Codes

- Error Correcting Output Codes
- Codebook for classes (binary codes)
- Learn instance codes using codebook as a multi-label problem



Output Codes: Shortcomings

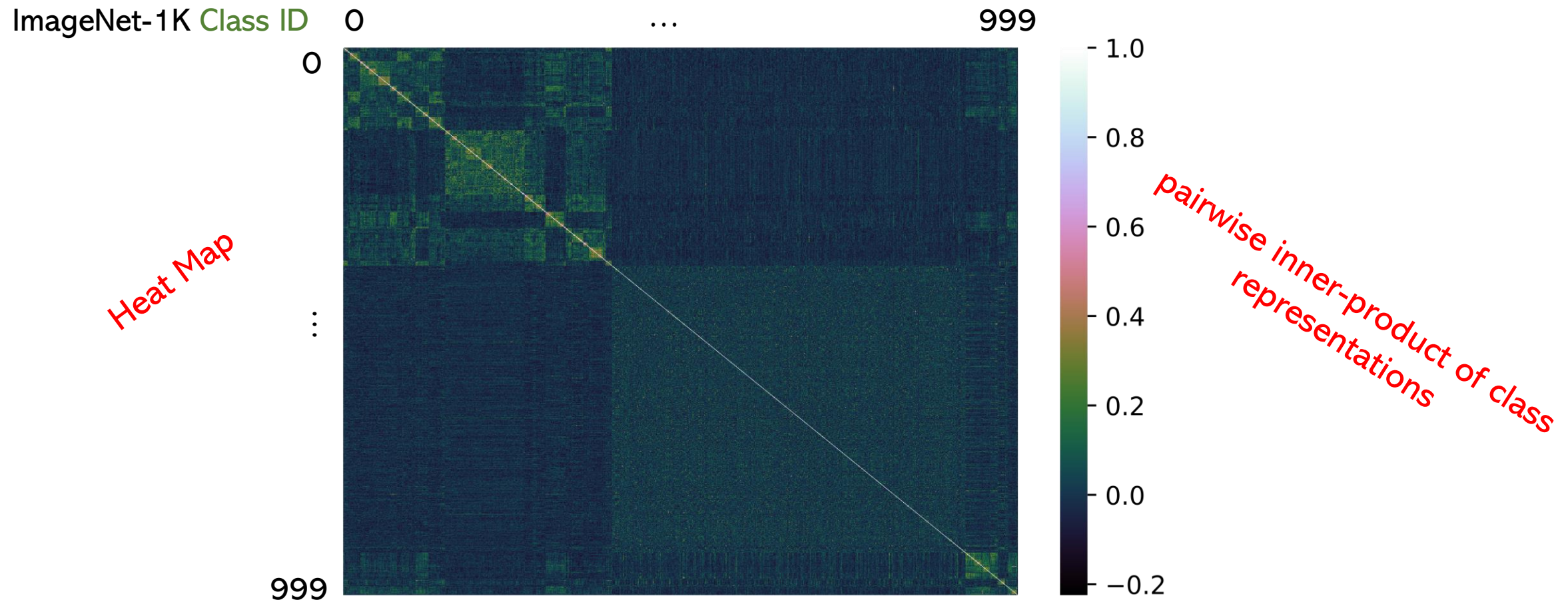
- Construction of output codes
 - Attributes / Hierarchy / Random
- Extremely hard to learn
 - Suffer from codebook collapse with most optimization techniques
- Inaccurate & often not tight - $O(\log L)$ with large constants



Can we learn accurate & tight output codes without using any side information?

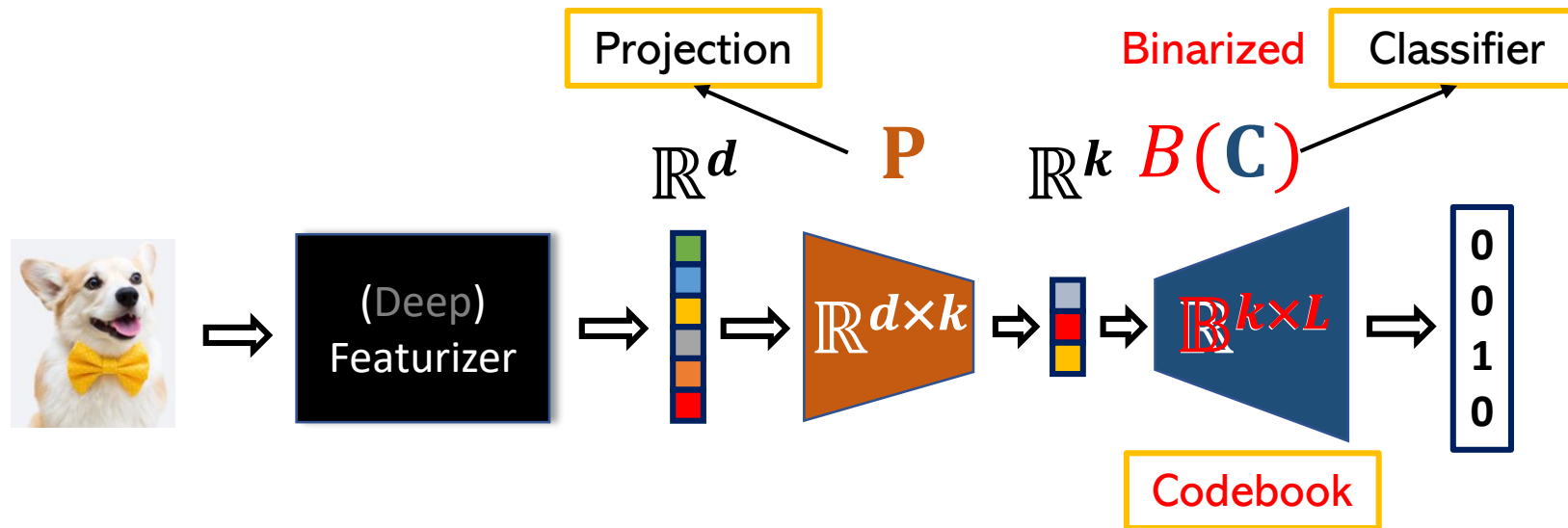
Key Obs.: Accurate Class Representations

- Classifier works great; ImageNet - **1000** (L) 2048-dim real vectors (\mathbb{R}^d)



Low-dimensional Class Codes

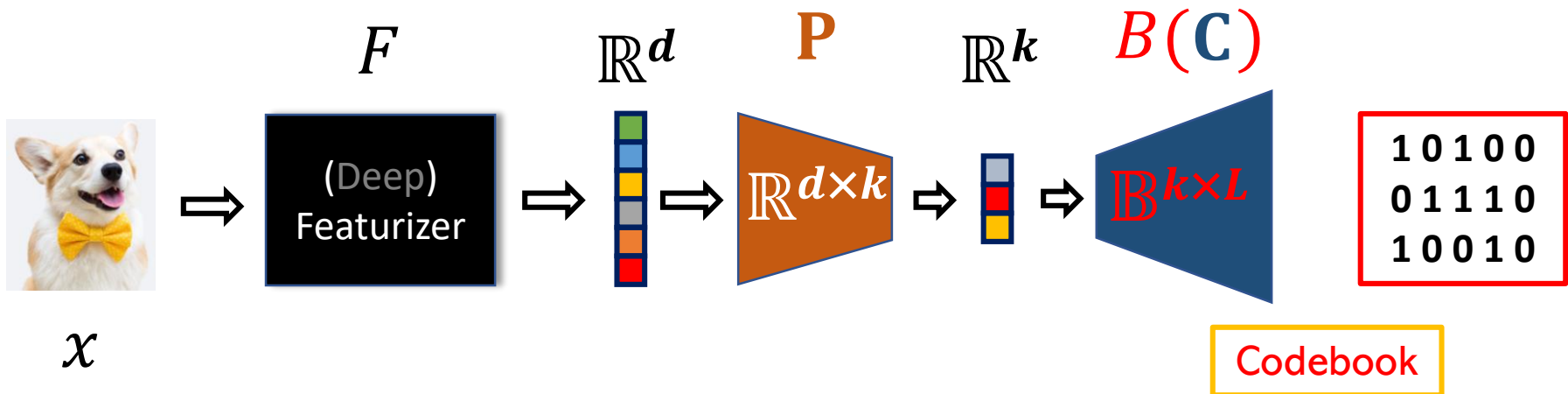
- Linear classifier on low-dimensional space (\mathbb{R}^k ; $k \approx \log(L) \ll d$)



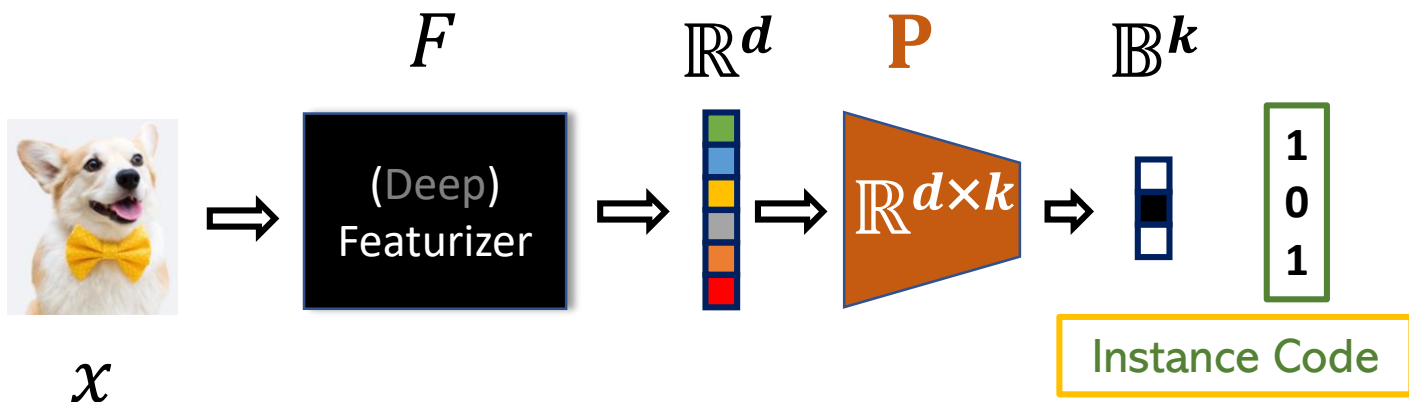
- Learn binarized ($\mathbb{B}^{k \times L}$) $\{0/-1, 1\}$ version of the linear classifier
- $B(\mathbf{C})$ is the collection of class codes aka **Codebook**

The LLC Method

- Phase 1 – Codebook Learning

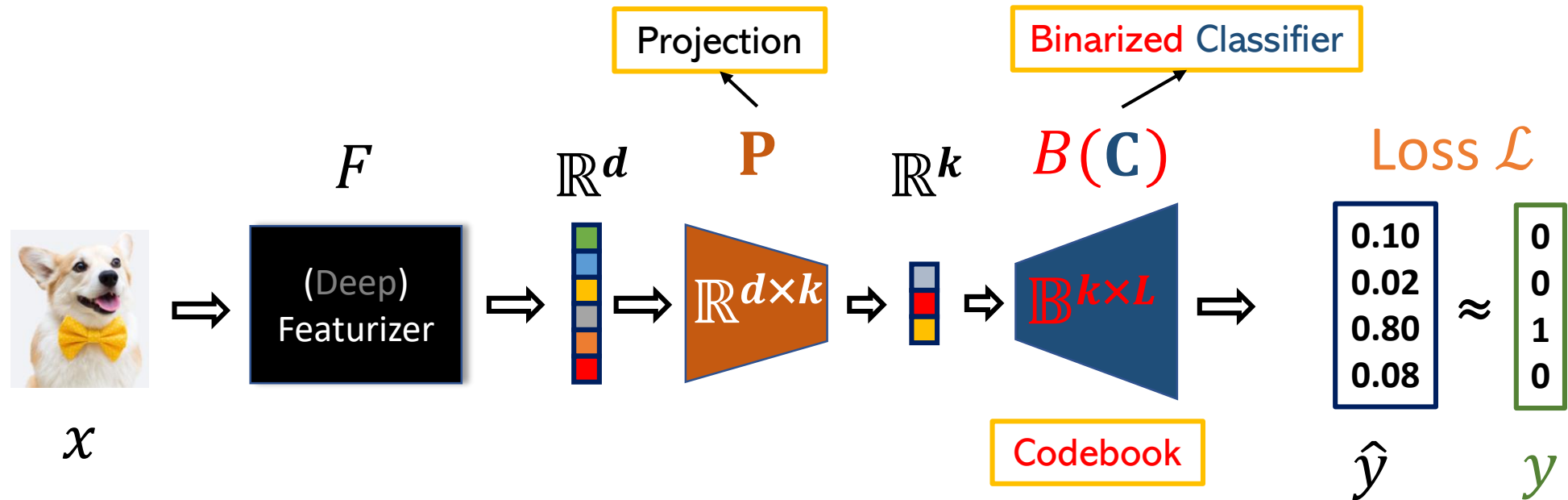


- Phase 2 – Instance Code Learning



LLC: Phase 1 – Codebook Learning

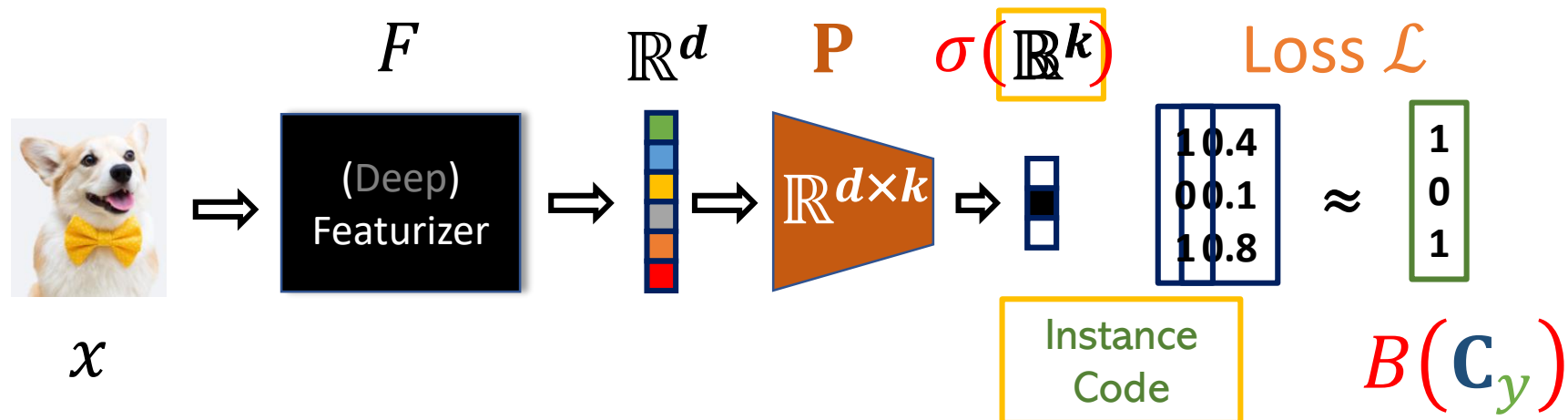
- Learnt end-to-end - F , \mathbf{P} & $B(\mathbf{C})$ - w/ Stochastic Gradient Descent (SGD)



- Binarization is learnt through Straight Through Estimator (STE)

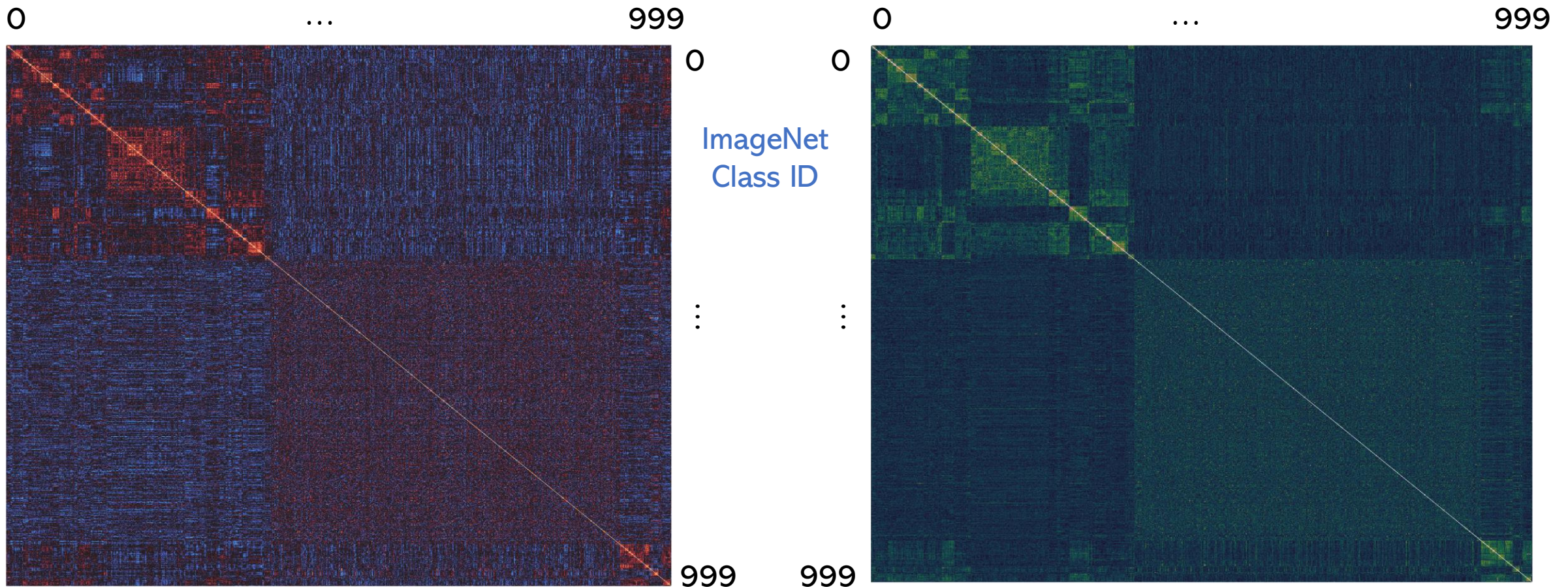
LLC: Phase 2 – Instance Code Learning

- Warm start w/ F , P : generate $k \approx \log(L)$ dim instance representation
- Columns of $B(\mathbf{C}) \in \mathbb{B}^{k \times L}$ - target output labels per class $B(\mathbf{C}_y)$
- Solve the multi-label problem as k binary classification problems
- Binarize the multi-label predictions to obtain instance codes (\mathbb{B}^k)



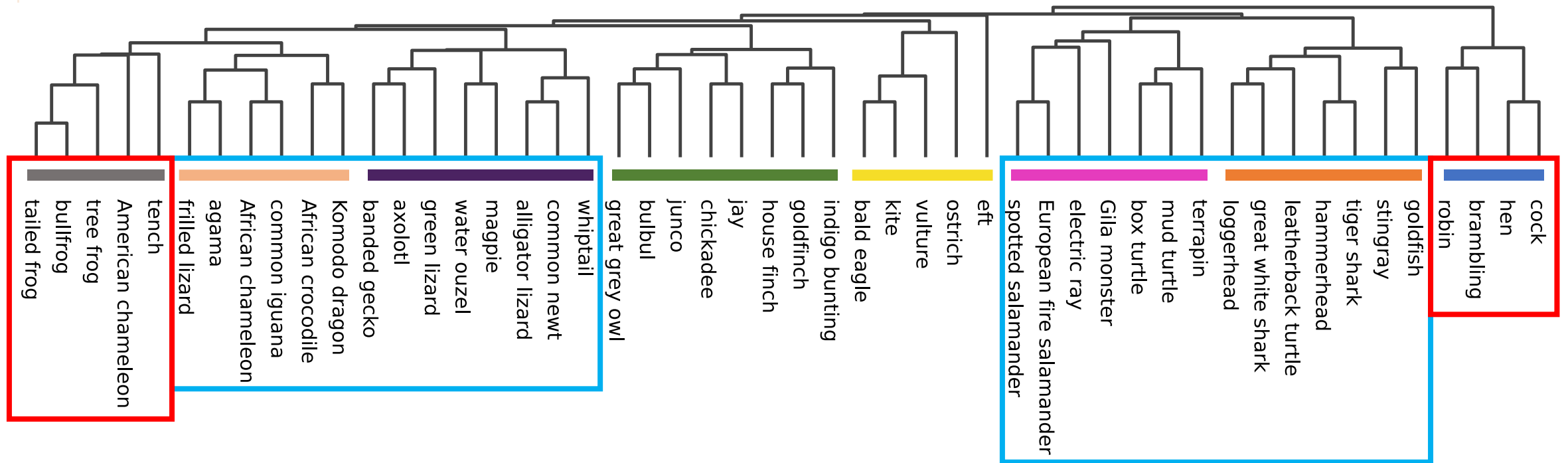
Heat Maps: Comparison for ImageNet-1K

- 20-bits produce a visually similar heat map as 2048-dim real numbers



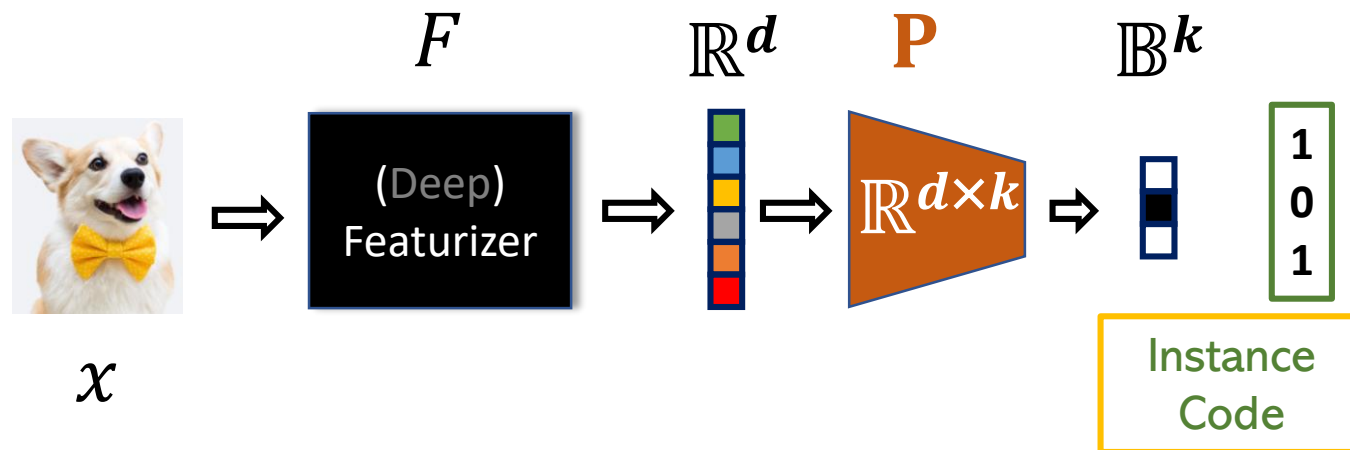
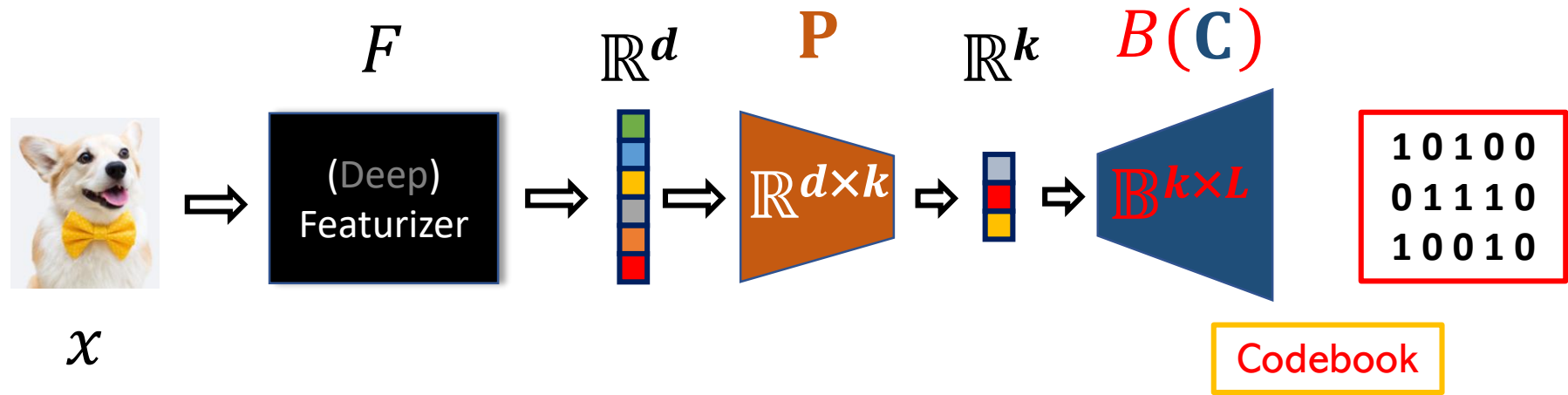
Discovered Taxonomy: 20-bit Codebook

- Agglomerative clustering builds an intuitive hierarchy
- 20-bits capture important high-level semantic information



Discovered Taxonomy for 50 classes of ImageNet-1K

LLC: Class & Instance Codes



LLC: Decoding Schemes for Classification

Exact Decoding (ED):

- Instance code needs to exactly match the ground truth class code

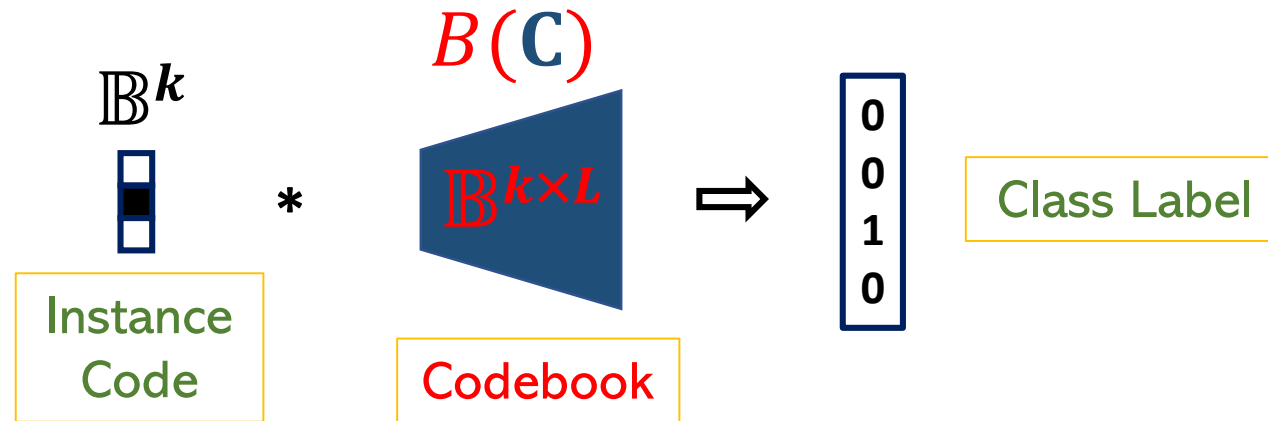


- Extremely efficient – Scales as $O(k \approx \log L) + O(1)$ hash lookup

LLC: Decoding Schemes for Classification

Minimum Hamming Decoding (MHD):

- Retrieves the closest class code for an instance code using Hamming distance



- Efficient - Scales as $O(k * L)$ instead of the typical $O(d * L * r)$

r is the relative cost of real-valued compute over bits

LLC: Applications

- Efficient Multiclass Classification

- ImageNet-1K with 20 bits
- Multiple decoding schemes for compute and accuracy trade-offs

- Efficient Retrieval

- ImageNet-100 with 10 bits
- Potential for low-latency high recall retrieval in search systems

- Out-of-Distribution (OOD) Detection

- Out-of-the-box without tuning for threshold

LLC: Image Classification for ImageNet-1K

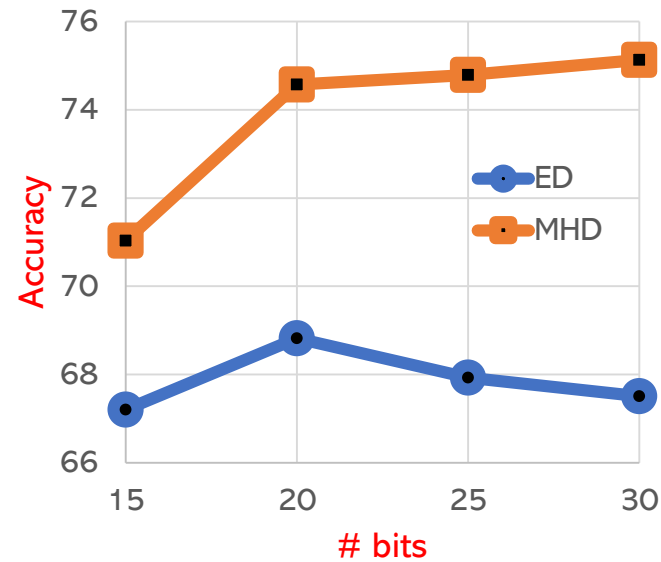
- Comparison across 20-bit codebooks using ResNet50 backbone

Codebook	# Unique Codes	ED Accuracy (%)	MHD Accuracy (%)
Random	1000	64.07	66.91
CCA	813	55.17	57.03
SVD	969	65.12	69.18
LLC (Ours)	1000	68.82	74.57

- LLC learns more accurate, tight & reliable codebooks
- ResNet50 with 2048-dim real representation + linear classifier: **77%**

LLC: Image Classification for ImageNet-1K

- Classification accuracy vs. # bit codes for LLC on ResNet50 backbone



- MHD accuracy \uparrow s gradually; but ED accuracy \uparrow s & \downarrow s
 - LLC gets only 19.2 & 28.5 bits right for 20 & 30 bit models respectively

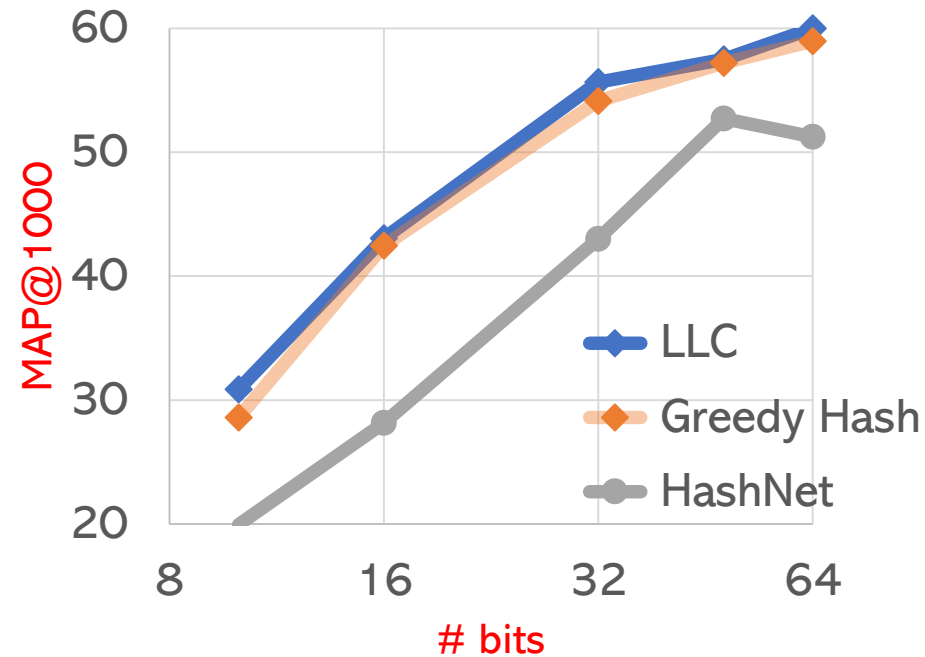
LLC: Image Retrieval for ImageNet-100

- Encode the image and database using instance binary codes
- For a query image, retrieve images of the same class
- MAP@1000 performance for retrieval using ResNet50 backbone

Representation	8 dims	10 dims	64 dims
LLC (1-bit)	-	64.07	67.73
Real (16-bits)	50.41	66.57	77.94

LLC: Image Retrieval for ImageNet-100

- MAP@1000 vs # bits comparison for retrieval using AlexNet backbone



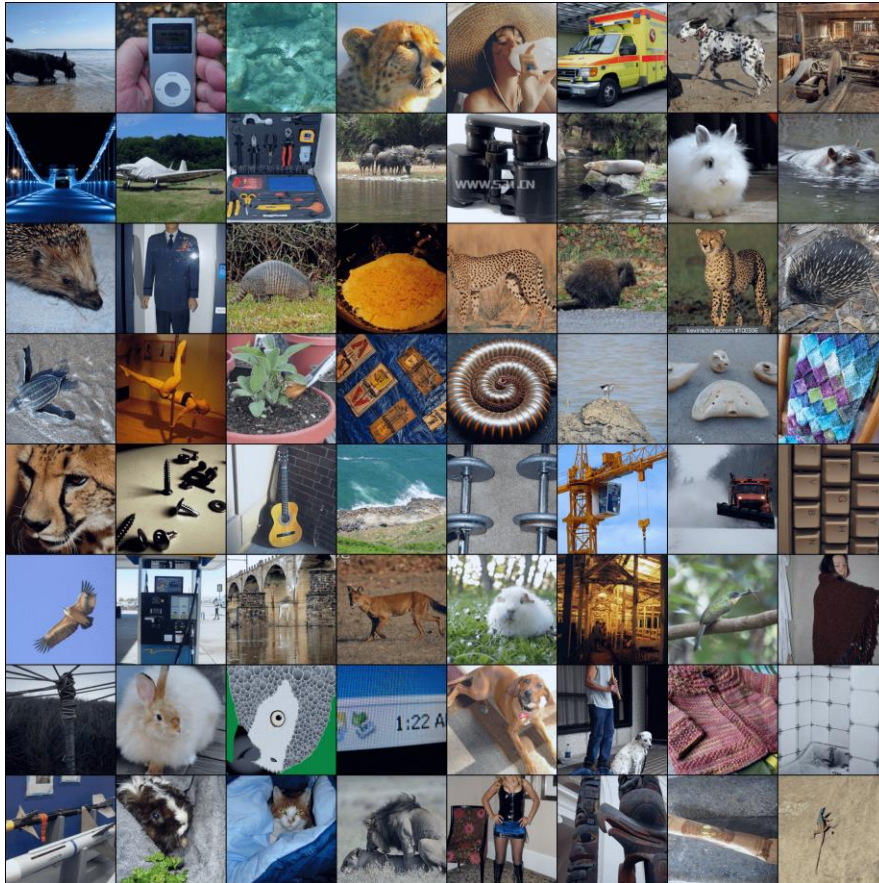
- Baselines are designed to learn only instance codes

LLC: Ablations

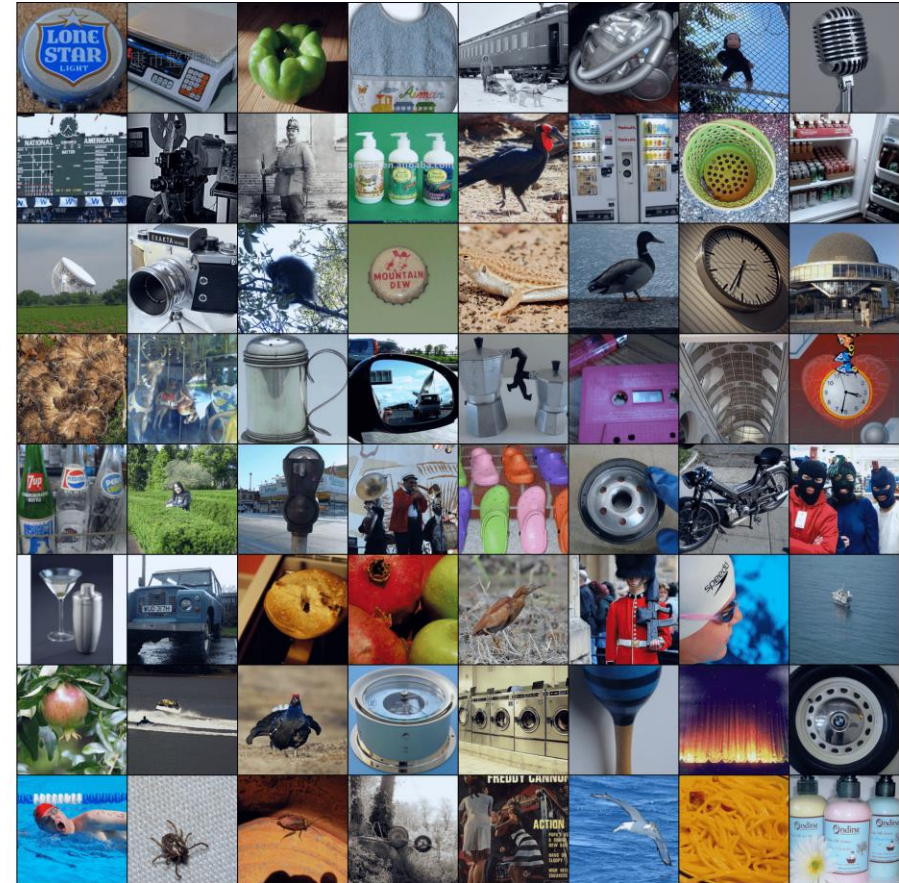
- **Faster codebook learning**
 - Cheaper backbones; lesser data
 - Warm start with collapsed SVD/CCA codebooks
- **Linear vs. Hamming separability**
 - LLC makes representation Hamming separable (hypercube)
 - Hamming separability (more efficient) → Linear separability (more accurate)
- **Nested codebook learning**
 - Train a 30-bit codebook, get 20-bit and 25-bit codebooks for free
 - Extremely useful in deployment across various budgets without retraining

LLC: Are Learnt Codes Interpretable? **NO!**

Bit 4



1



0

LLC: Conclusions

- First method to learn both **class** & **instance** codes simultaneously
- Learns semantically rich, highly accurate & tight binary codes reliably
- Enables applications like *classification & retrieval* in sub-linear costs
- **Future Work:**
 - Million-Billion scale classification & retrieval for search / instance classification
 - Extremely efficient edge classifiers for tiny devices
 - Cross-modal representation learning for interpretability in sub-linear costs
 - Binary representations for various domains like videos, controls etc.,