Learning Deep Representation for Imbalanced Classification

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Motivation

- Data imbalance in vision classification

Wearing hat

Minority class

Not wearing hat

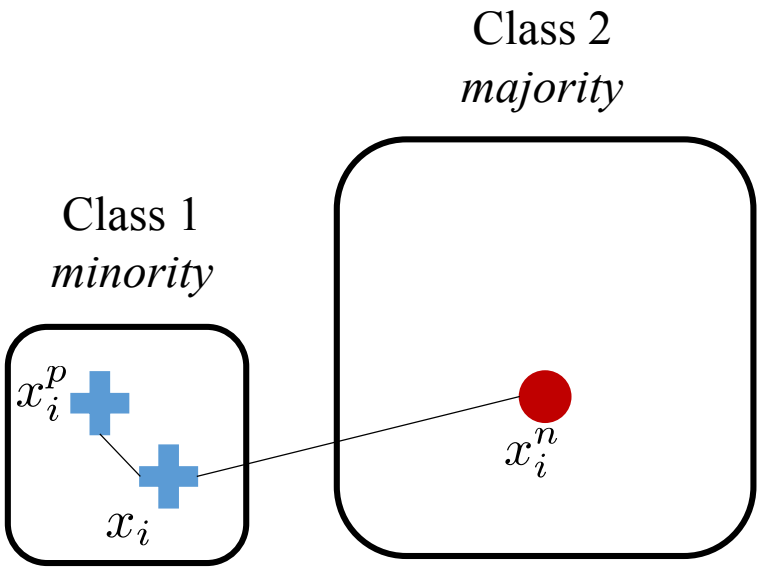
Majority class

...

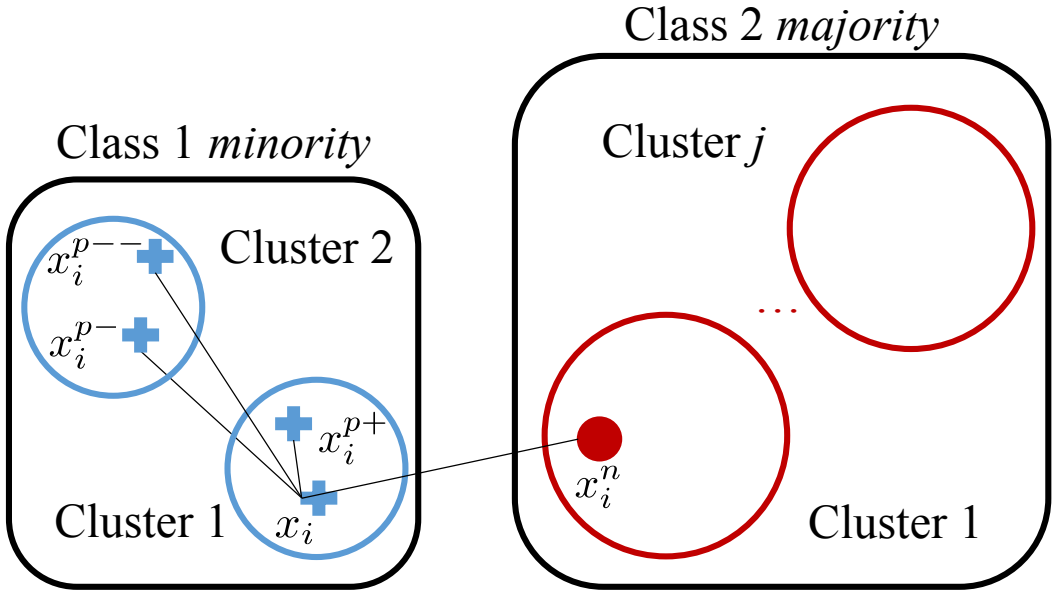
Motivation

- Deep embedding: **Class-level** → **cluster- & class-level** constraint

Triplet embedding



Quintuplet embedding



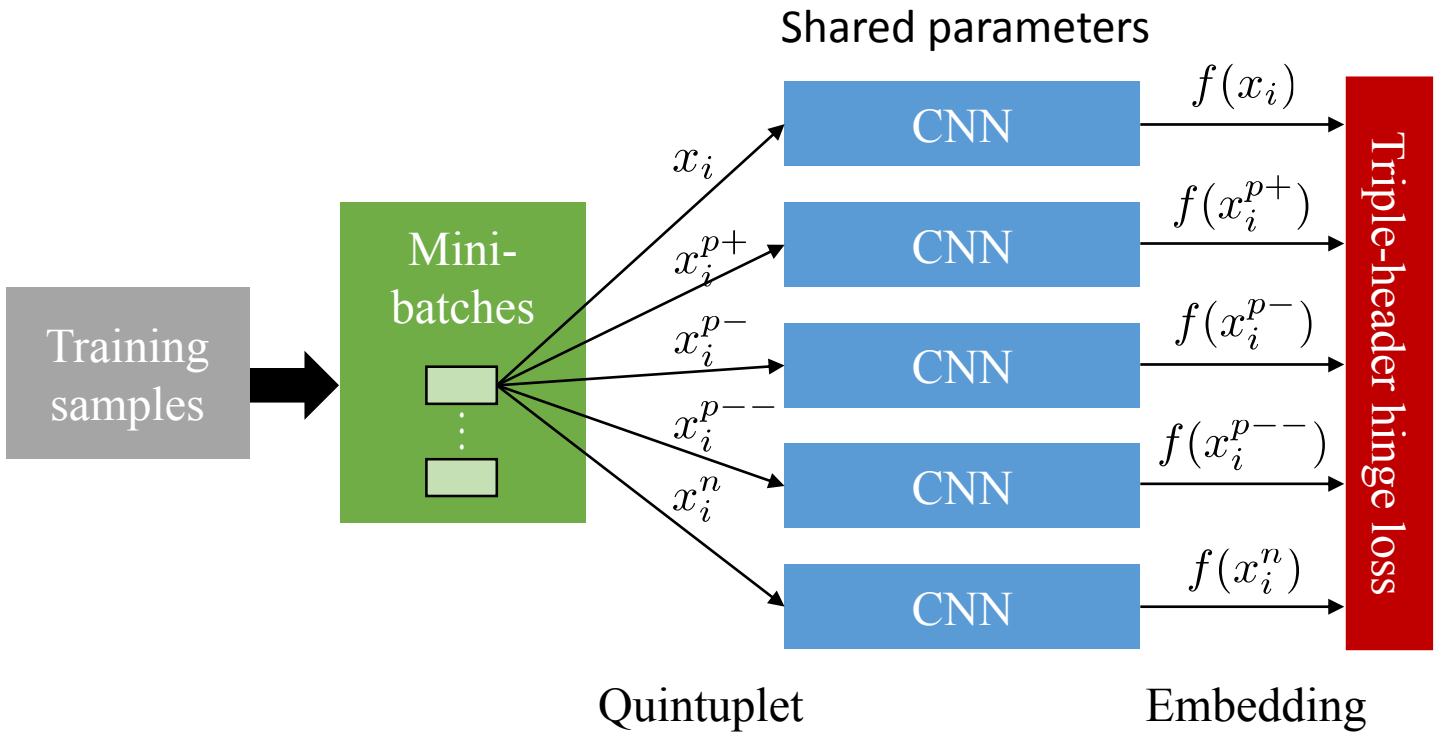
$$D\left(f(x_i), f\left(x_i^p\right)\right) < D(f(x_i), f(x_i^p))$$

$$D\left(f(x_i), f\left(x_i^{p+}\right)\right) < D(f(x_i), f(x_i^{p-})) < D(f(x_i), f(x_i^{p--})) < D(f(x_i), f(x_i^n))$$

- Study traditional **re-sampling** [ICML'03] and **cost-sensitive learning** [ICDM'03] scheme

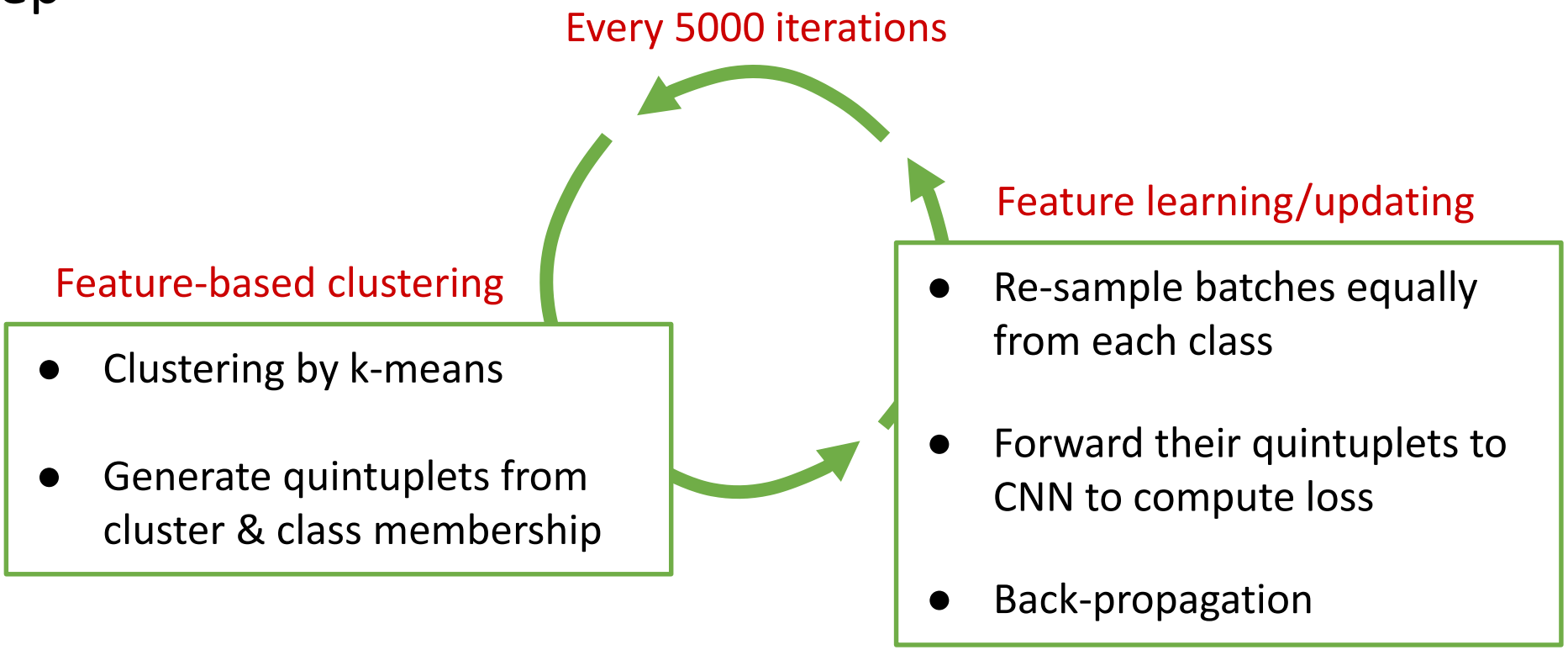
Large Margin Local Embedding

- Network architecture
  - Equal class re-sampling & class costs assignment in batches



Large Margin Local Embedding

- Training step



- Cluster-wise kNN search

$$y_q = \arg\max_{c=1,\ldots,C} \left(\min_{\substack{m_j \in \phi(q) \\ y_j \neq c}} D(f(q), f(m_j)) - \max_{\substack{m_i \in \phi(q) \\ y_i = c}} D(f(q), f(m_i)) \right)$$

Results

- Large-scale CelebA face attributes dataset
  - **200K** celebrity images, each with **40** attributes
  - Highly imbalanced: average positive class rate **23%**

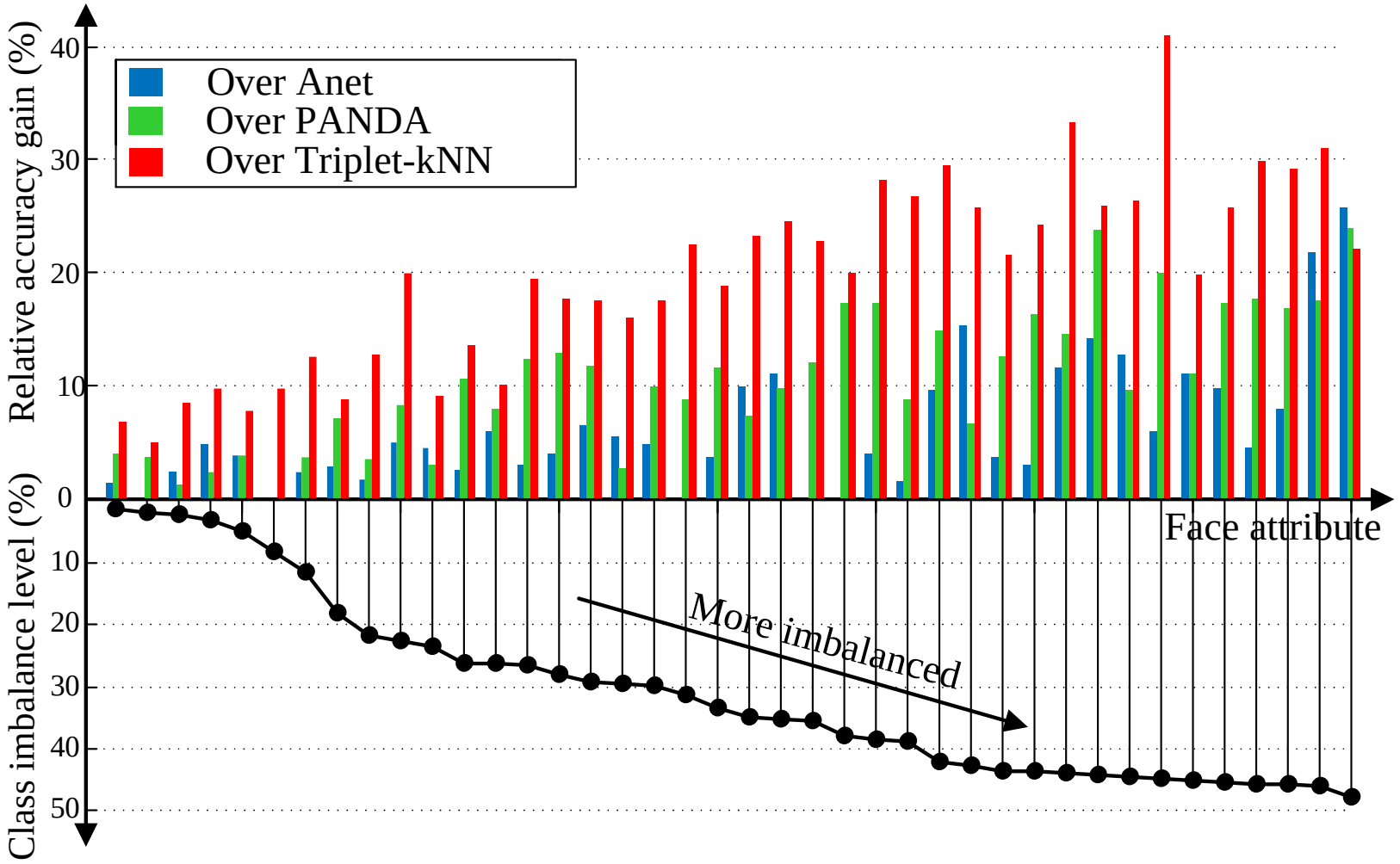
- We adopt a balanced accuracy
  - $total\ accuracy = \left(\frac{tp + tn}{Np + Nn}\right)$
  - $balanced\ accuracy = \frac{1}{2}\left(\frac{tp}{Np} + \frac{tn}{Nn}\right)$

	Total acc.	Balanced acc.
Triplet-kNN*	83	72
Anet+	87	80
LMLE-kNN	**90**	**84**

*[Schroff et al., CVPR15] +[Liu et al., ICCV15]

Results

- Relative gains w.r.t. class imbalance



Take-home message

- Learning deep feature embedding for imbalanced data classification
- Cluster- and class-level quintuplets can preserve both locality across clusters and discrimination between classes, irrespective of class imbalance
- Large margin classification via fast cluster-wise kNN search