Motivation

- Bad performance due to problems in data.
- Powerful and straightforward deep learning models not able to use classical imbalance learning strategies.
- Different levels of imbalance:
  - The number of attributes per image is different.
  - The problem of unrepresented classes or ‘attribute-value’ combinations.
  - Inconsistency of labels/classes pairs given by annotators which are very subjective, different, and can be incorrect.

Proposed Strategies

Adaptations for different levels of imbalance:
- Class-level attribute transfer: Total and partial adaptations for two classical imbalanced strategies:
  - Sampling: Modifying the strategy to create batches → two different strategies to assign weights for samples.
  - Cost-sensitive learning: Assigning weights to each class. Specialized loss function (Focal Loss)

Conclusions

- Study of a fine-grained attribute classification problem with CUB imbalanced database as our main use case.
- Most bad performance problems are due to the data itself.
- Straightforward deep learning models offer suitable performances.
- Adapted strategies for different levels of imbalance.
- Adapted strategies concerning ‘Sampling’ and ‘Cost-Sensitive Learning’ approaches (same weights to all samples but with replacement).
- Loss function suitable to the imbalanced problem (Focal Loss).