

# Multilabel reductions

What is my loss optimising?

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# Multilabel classification

Given an instance, predict a **binary label vector**:



1

1

0

0



0

1

0

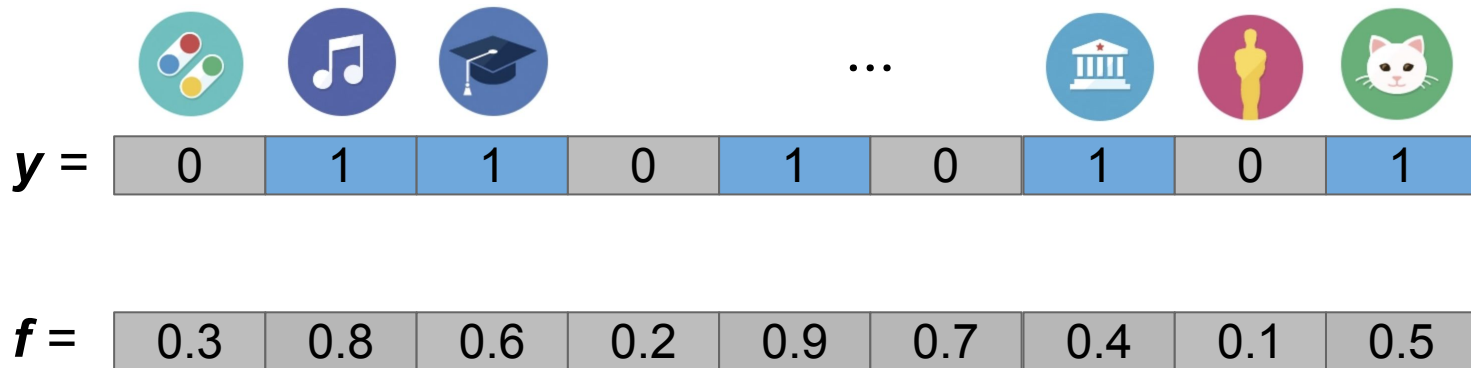
1

# Multilabel predictions

Multilabel observations:  $(x, \mathbf{y})$  where  $\mathbf{y} \in \{0, 1\}^L \rightarrow$  # of labels

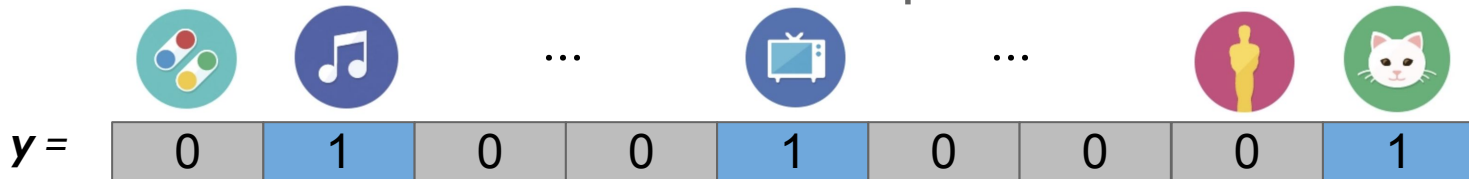
predictions:  $f(x) \in \mathbb{R}^L$

Want to assign high scores to positive labels ( $y_i = 1$ )



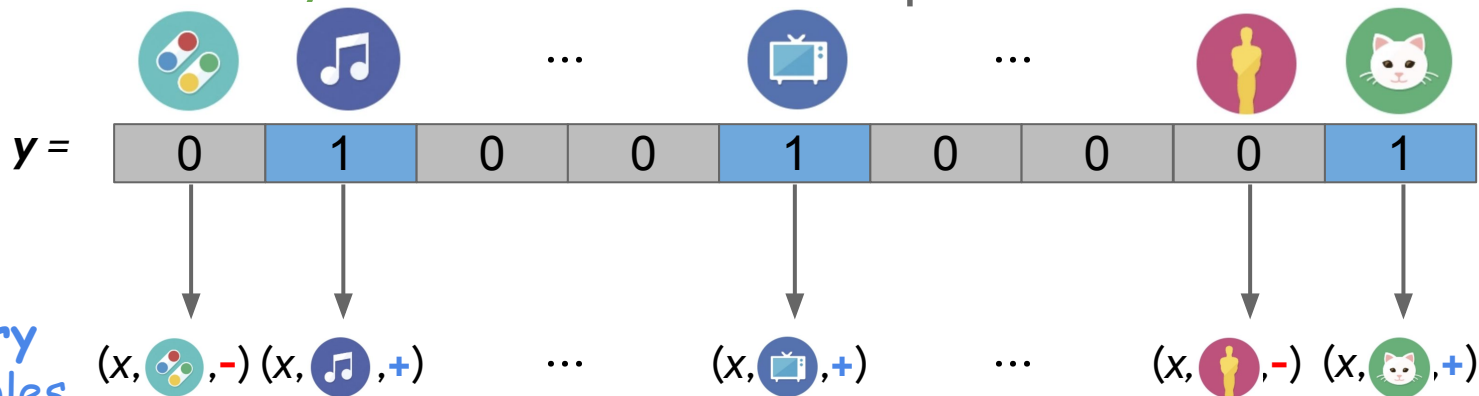
# Multilabel algorithm: **one-versus-all**

Create a **binary-classification** example for each label



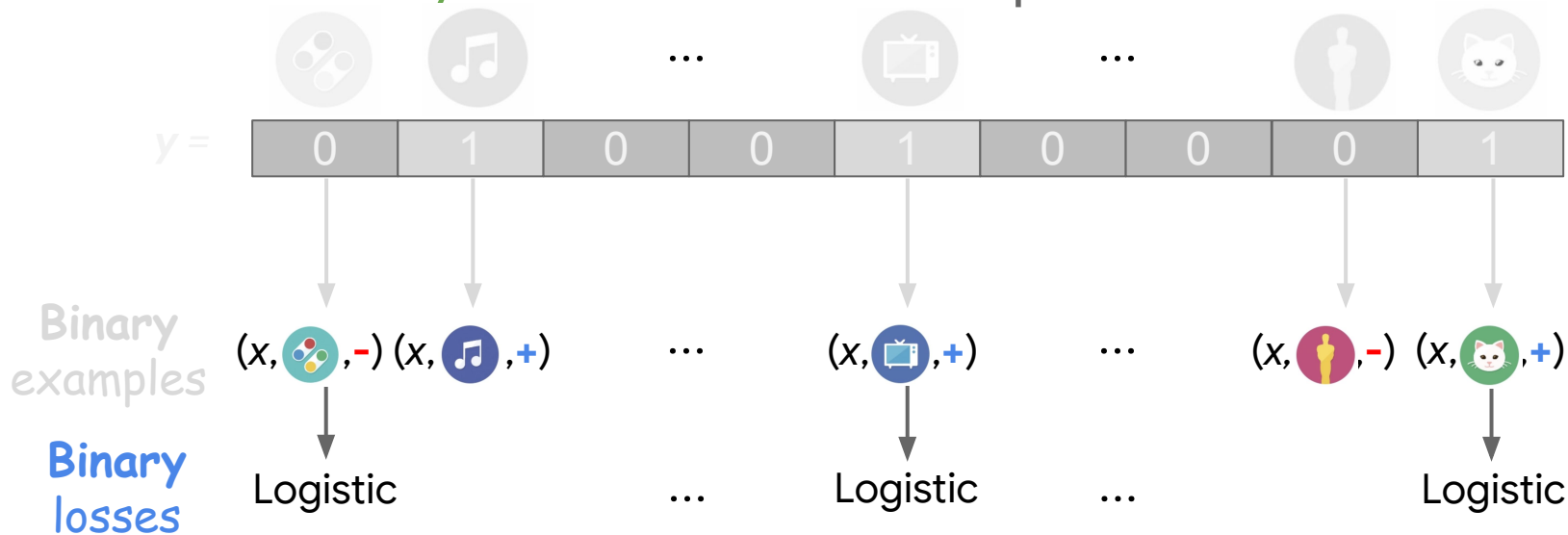
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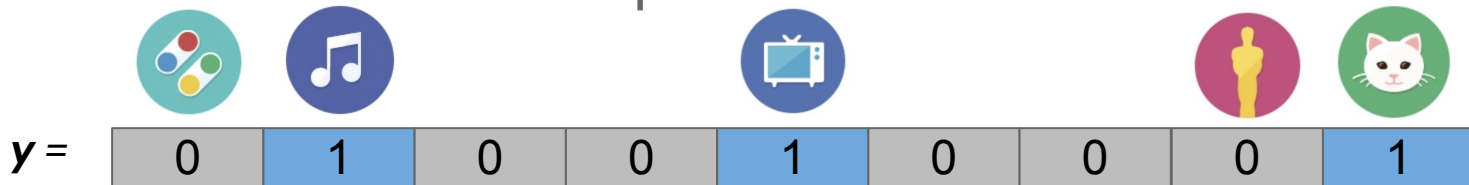
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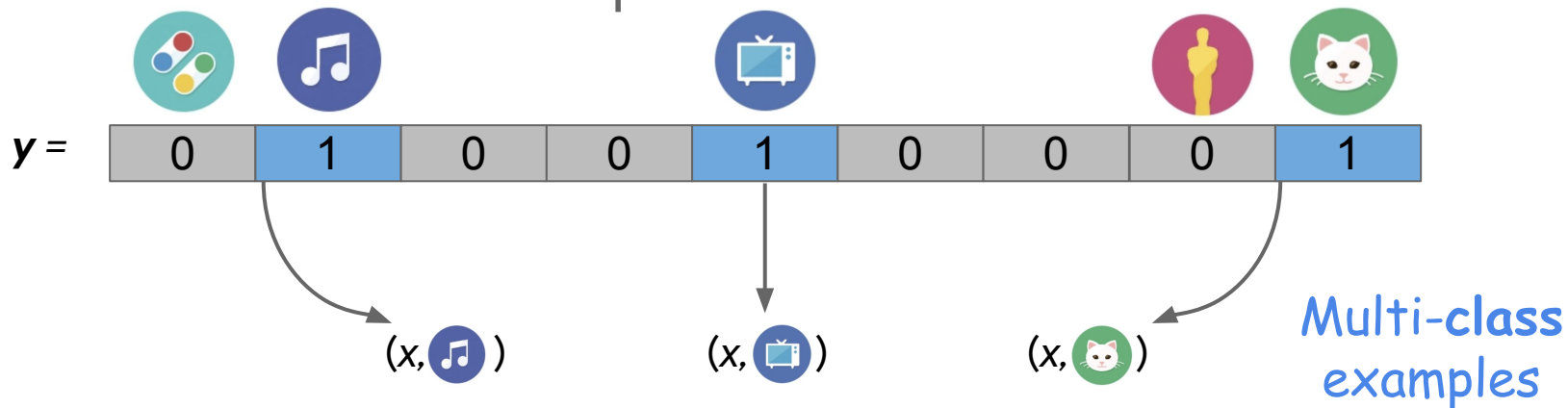
# Multilabel algorithm: **pick-all-labels**

Create a **multi-class** example for **each +ve label**



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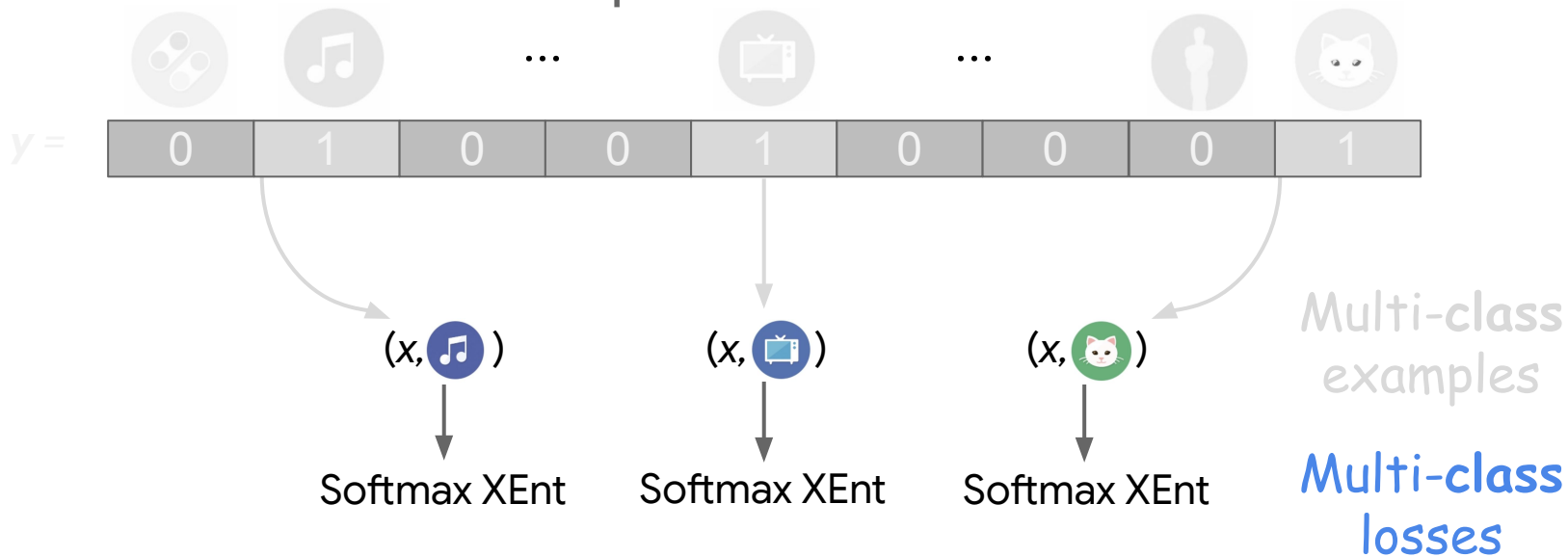
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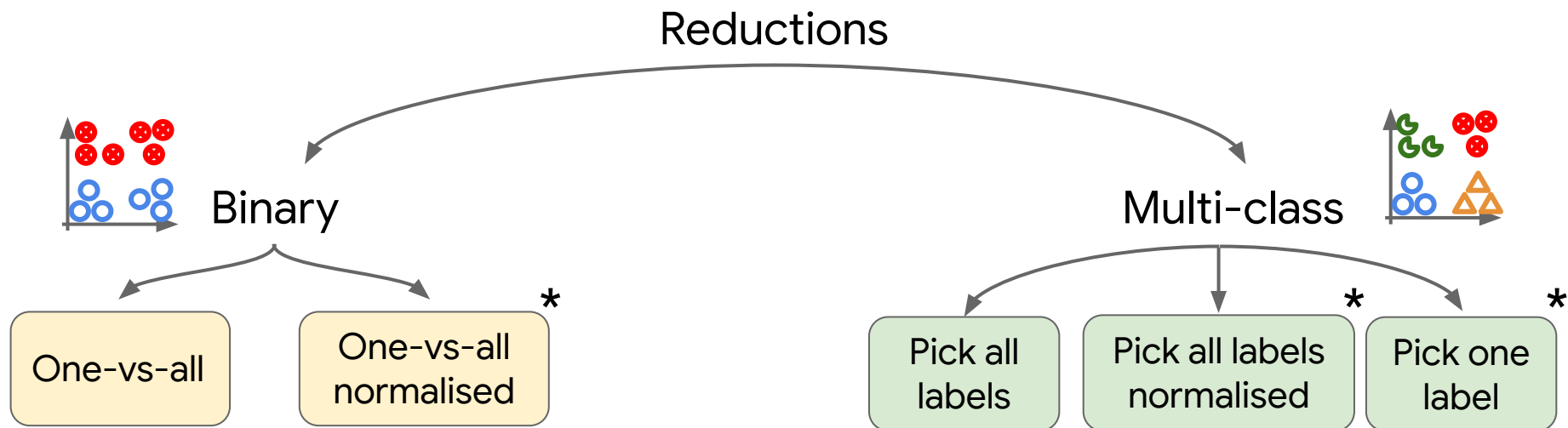


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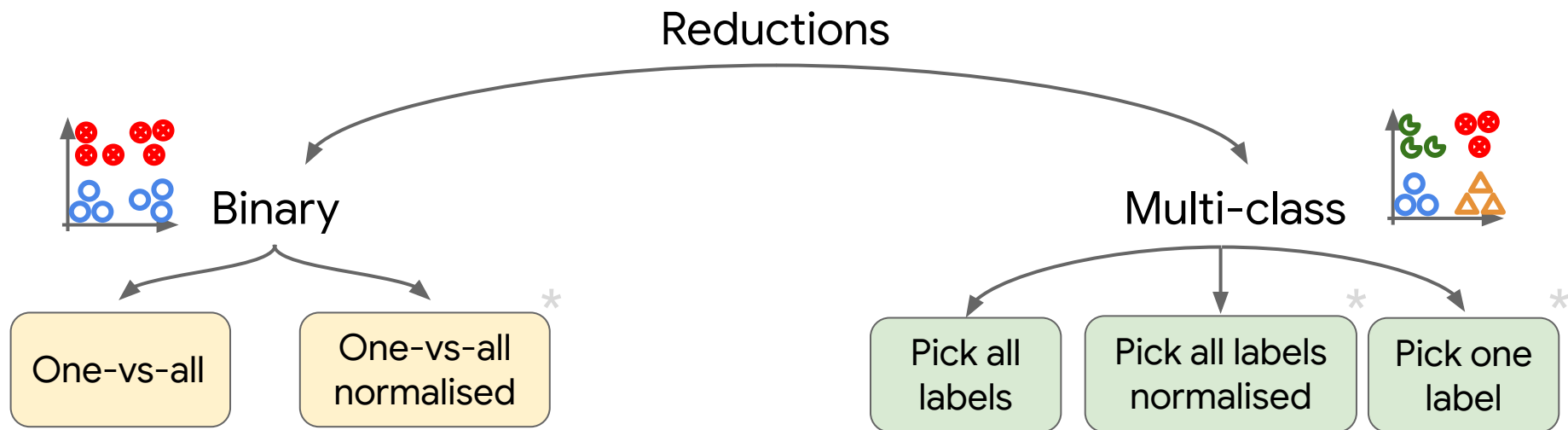


# Multilabel reduction landscape



\* See poster for details

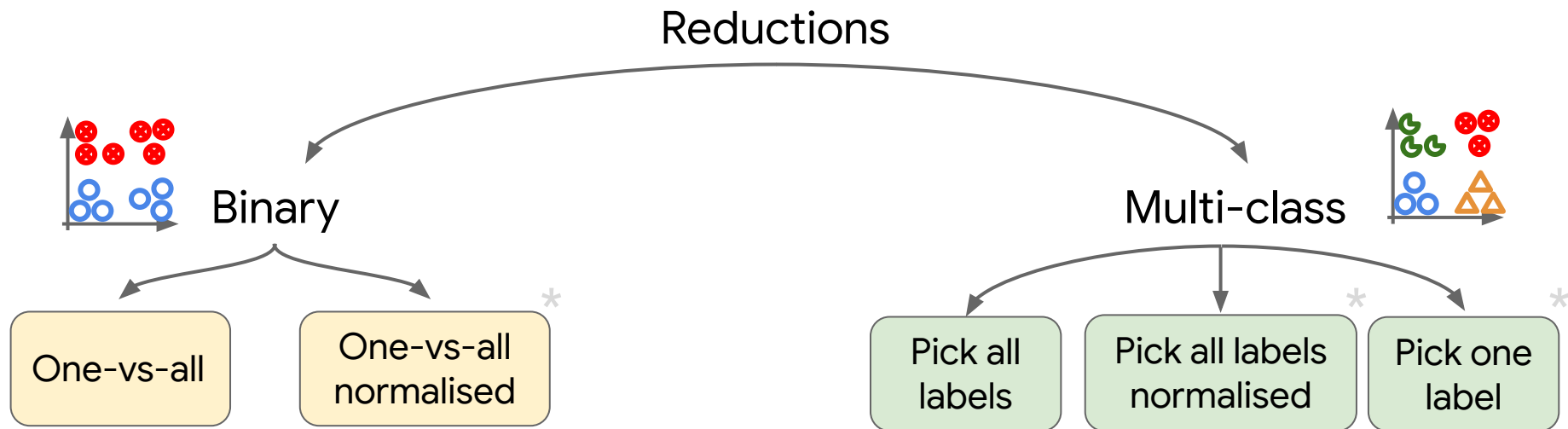
# Multilabel reduction landscape



✓ Leverage established losses

\* See poster for details

# Multilabel reduction landscape



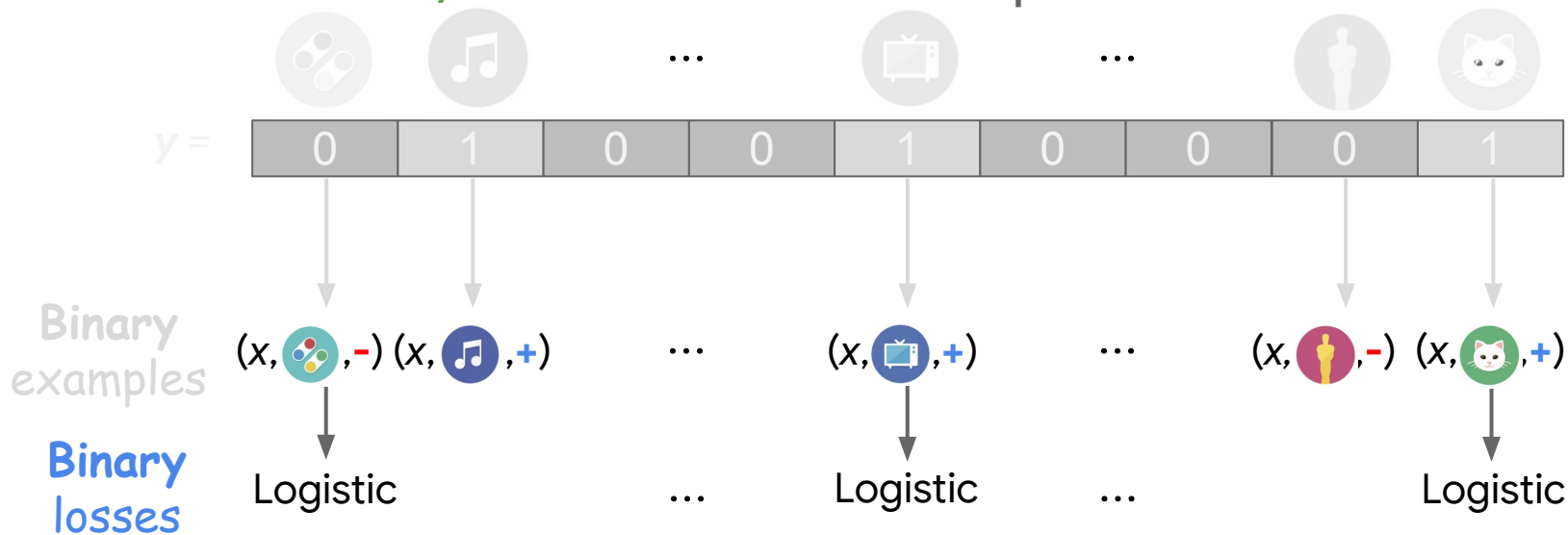
✓ Leverage established losses

✗ What do they optimise?

\* See poster for details

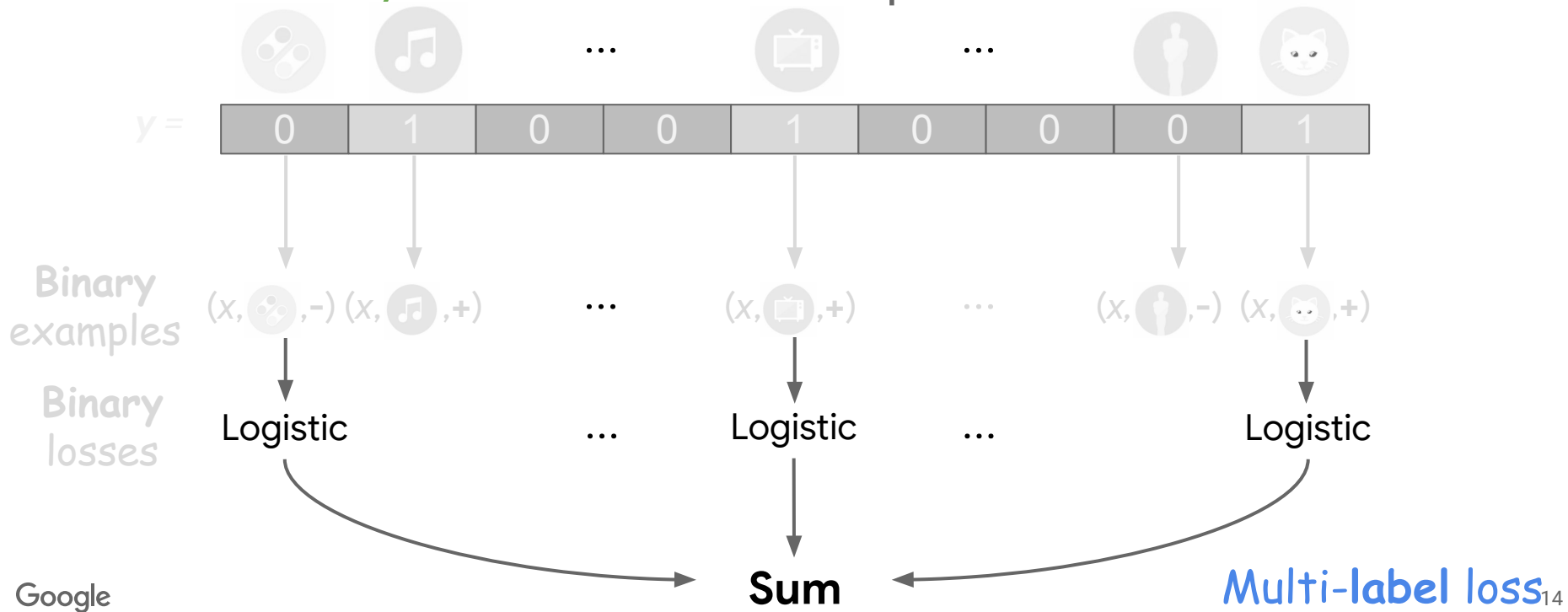
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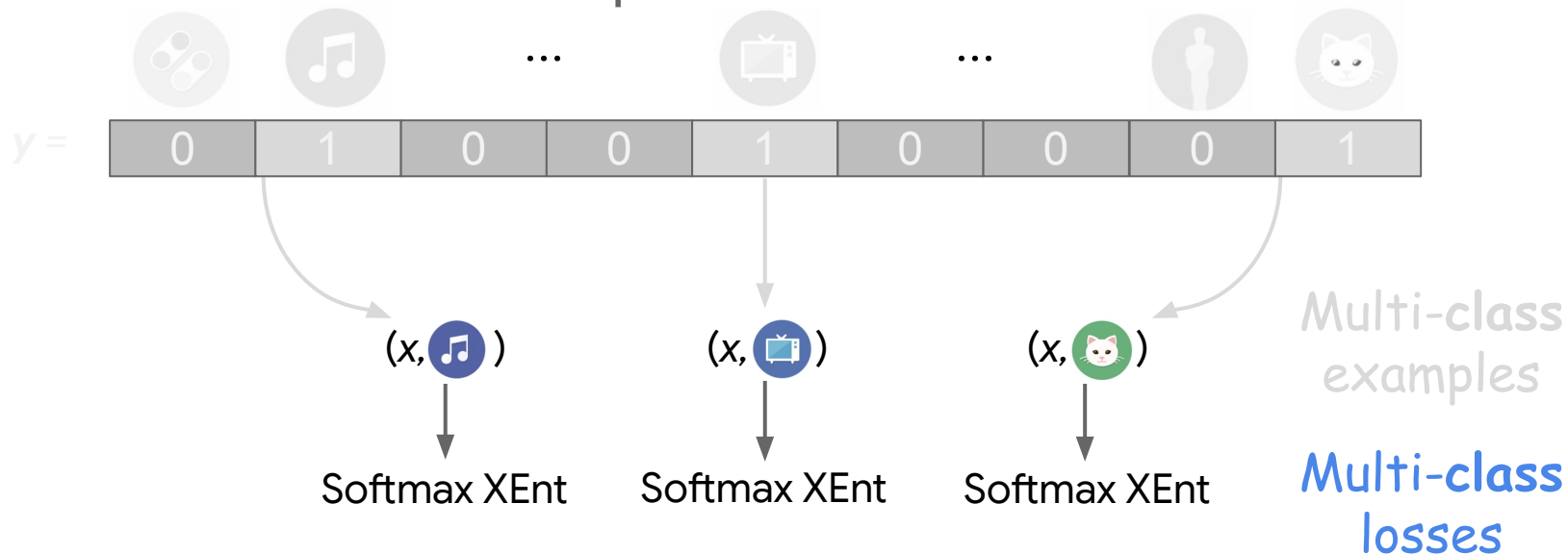
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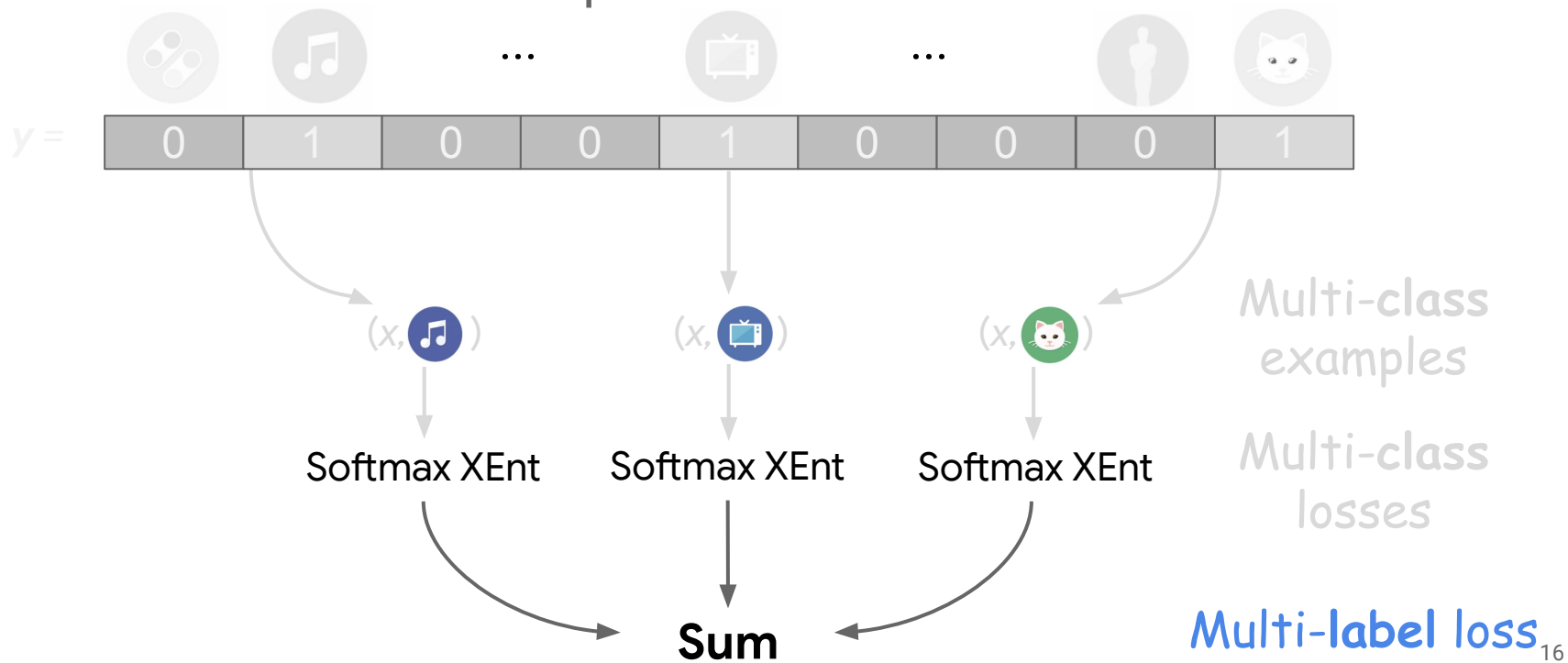
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Create a **multi-class** example for each **+ 've** label





# Bayes-optimal predictions

Bayes-optimal score for  $i$ th label is:

Reduction	Optimal score	
One-versus-all	$P(y_i = 1   x)$	Marginal label relevance
Pick all labels	$P(y_i = 1   x) / N(x)$	Expected # of +ve labels
All others	$P(y'_i = 1   x)$	"Normalised" label relevance

# Bayes-optimal predictions

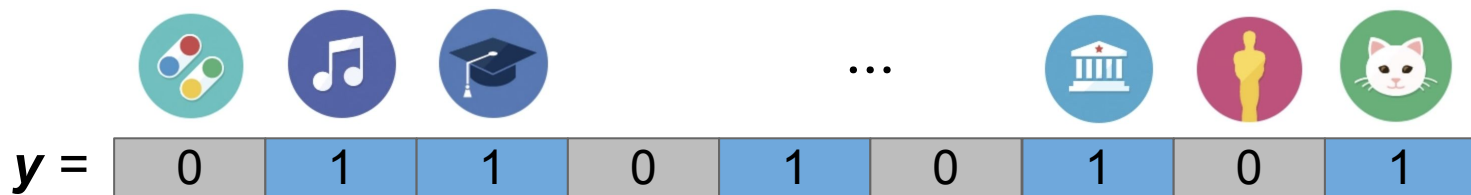
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“Pick all labels” scores **not coherent** across instances!

# Multilabel metrics

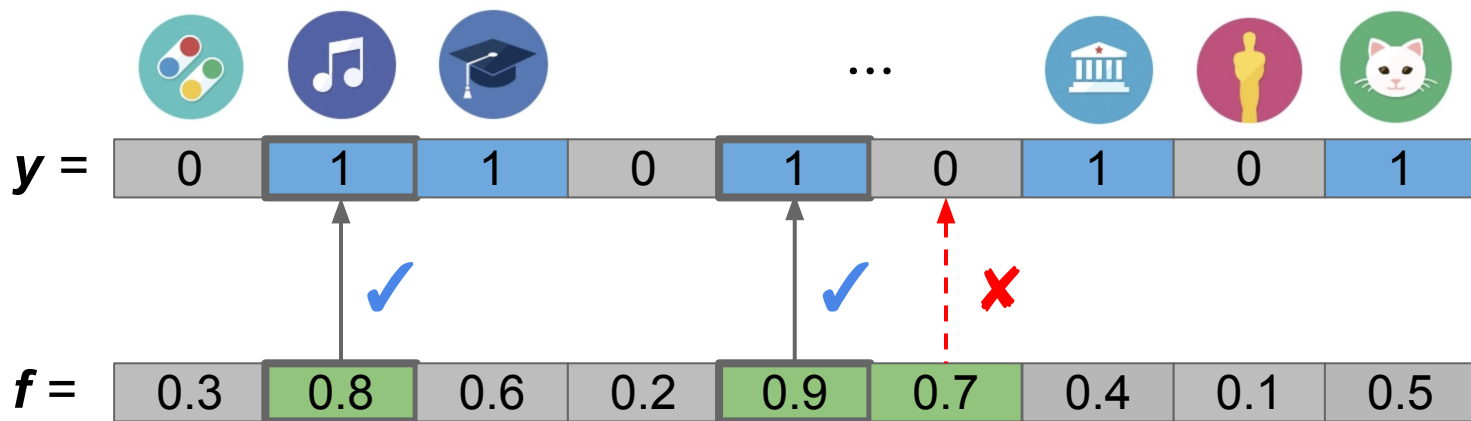
Evaluate predictions  $f \rightarrow$  find **top- $k$**  highest scoring indices



Here,  $k = 3$

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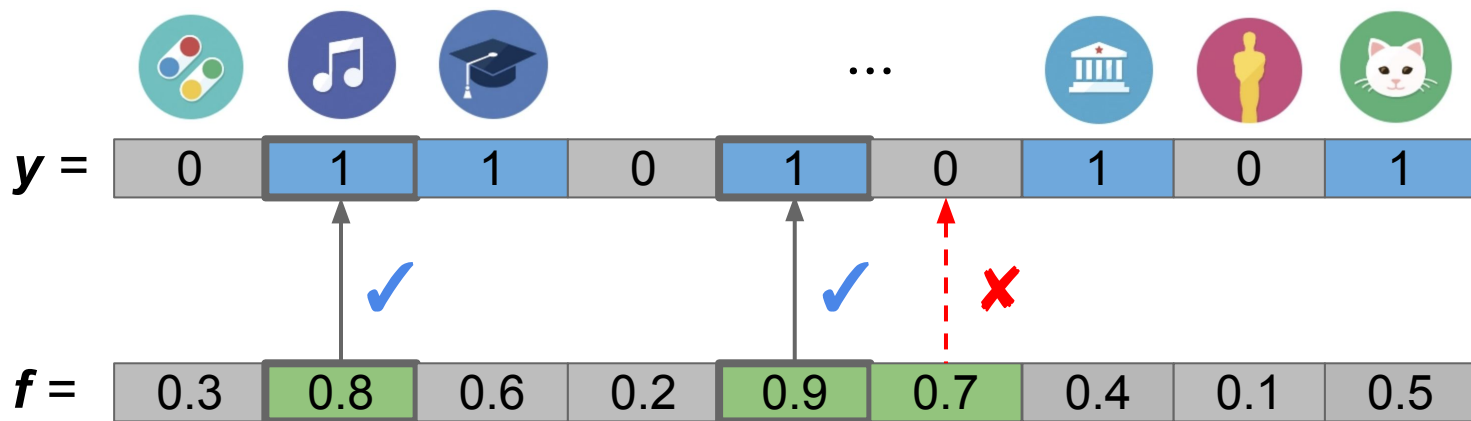


Here,  $k = 3$

$$\text{Precision@}k = \# \text{ positives in top-}k / k = 2/3$$

# Multilabel metrics

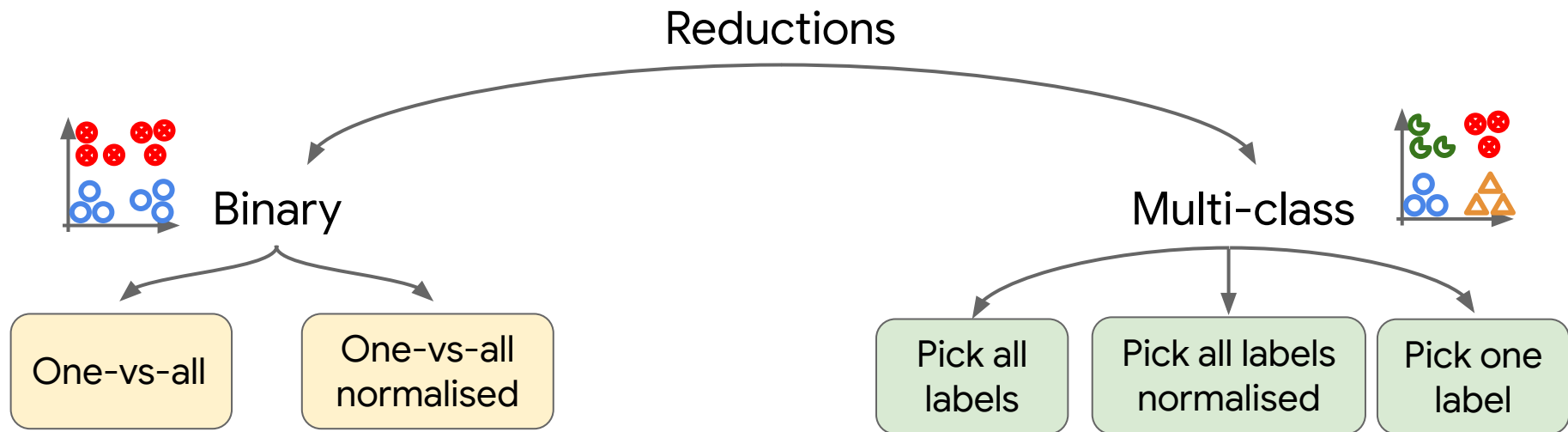
Evaluate predictions  $f \rightarrow$  find **top- $k$**  highest scoring indices



Here,  $k = 3$

$$\text{Recall@}k = \frac{\# \text{ positives in top-}k}{\# \text{ positives}} = \frac{2}{5}$$

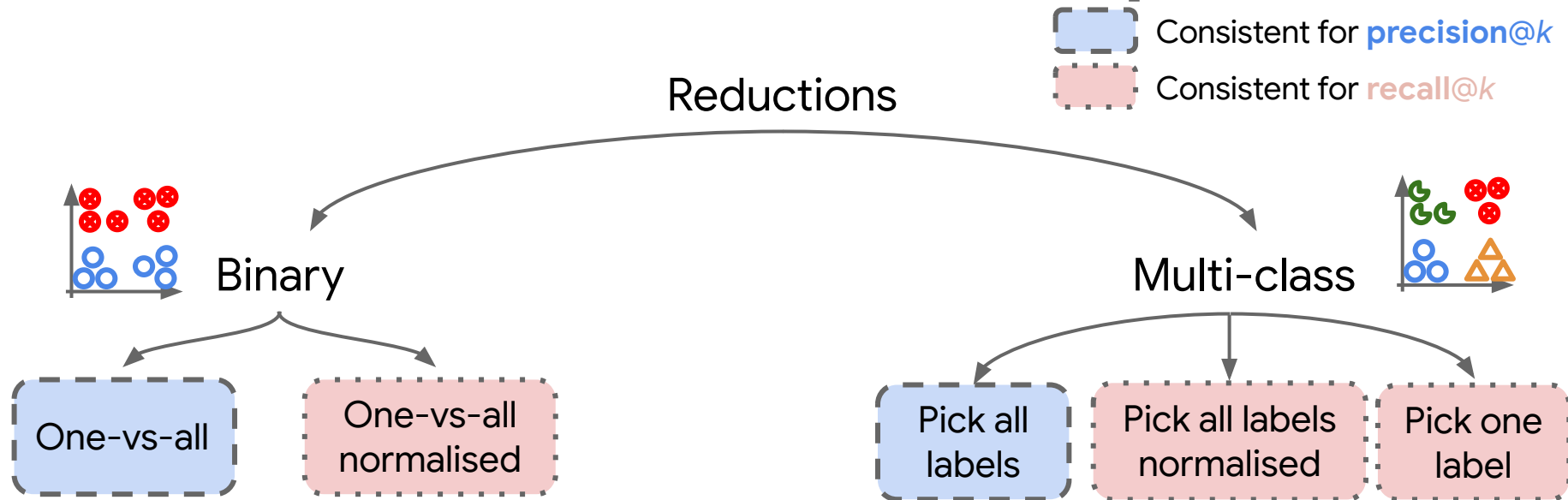
# Multilabel reduction landscape



✓ Leverage established losses

✗ What do they optimise?

# Multilabel reduction landscape



✓ Leverage established losses

✓ Consistent for precision or recall

# Drop by East Exhibition Hall B + C #14

Unified analysis of distinct multilabel reductions

Consistency for precision@k or recall@k -- but not both!

