Master Degree in Computer Science

Information Retrieval

Evaluation in information retrieval

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sed noli modo

Goals of evaluation

The goal of the evaluation activity is to **assess the quality of results obtained by an IR system**

The notion of *quality of results* depends on the task at hand, e.g.., search, classification, knowledge extraction, etc.

A general issue concerning the evaluation is that it is based on a **ground truth** (or **gold standard**), that is an **annotated corpus** where, for each document, we know if the document is **relevant** with respect to the task

Ground truth may be created by manually annotating documents and/or derived from data with a reference annotation system

Search evaluation: the notion of quality

Given a corpus ***C*** and a query ***q***, the task of document search is to find the set of documents $\boldsymbol{A_{q,C}}$ that match ***q***

We call $\boldsymbol{A_{q,C}}$ the **answers** to ***q***

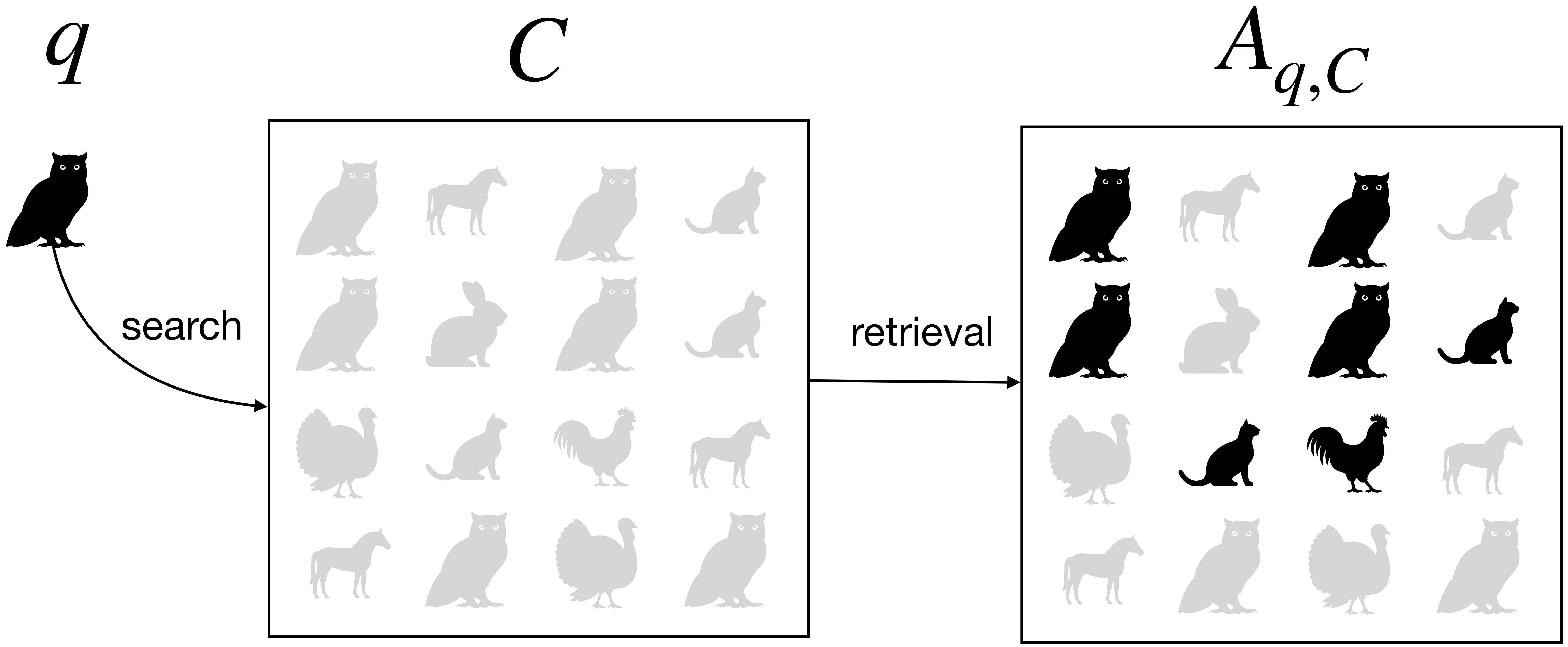
Question: when we say that the search answers $\boldsymbol{A_{q,C}}$ are good?

Search evaluation: the notion of quality

Question: when we say that the search answers ***A***$\boldsymbol{A_{q,C}}$ are good?

Definition 1: *when the documents contained in* $\boldsymbol{A_{q,C}}$ *are relevant to* ***q***

Remember: in order to know if a document is actually relevant, we need a **ground truth** (or a **user feedback**)



We retrieved 7 documents of which 4 are correct

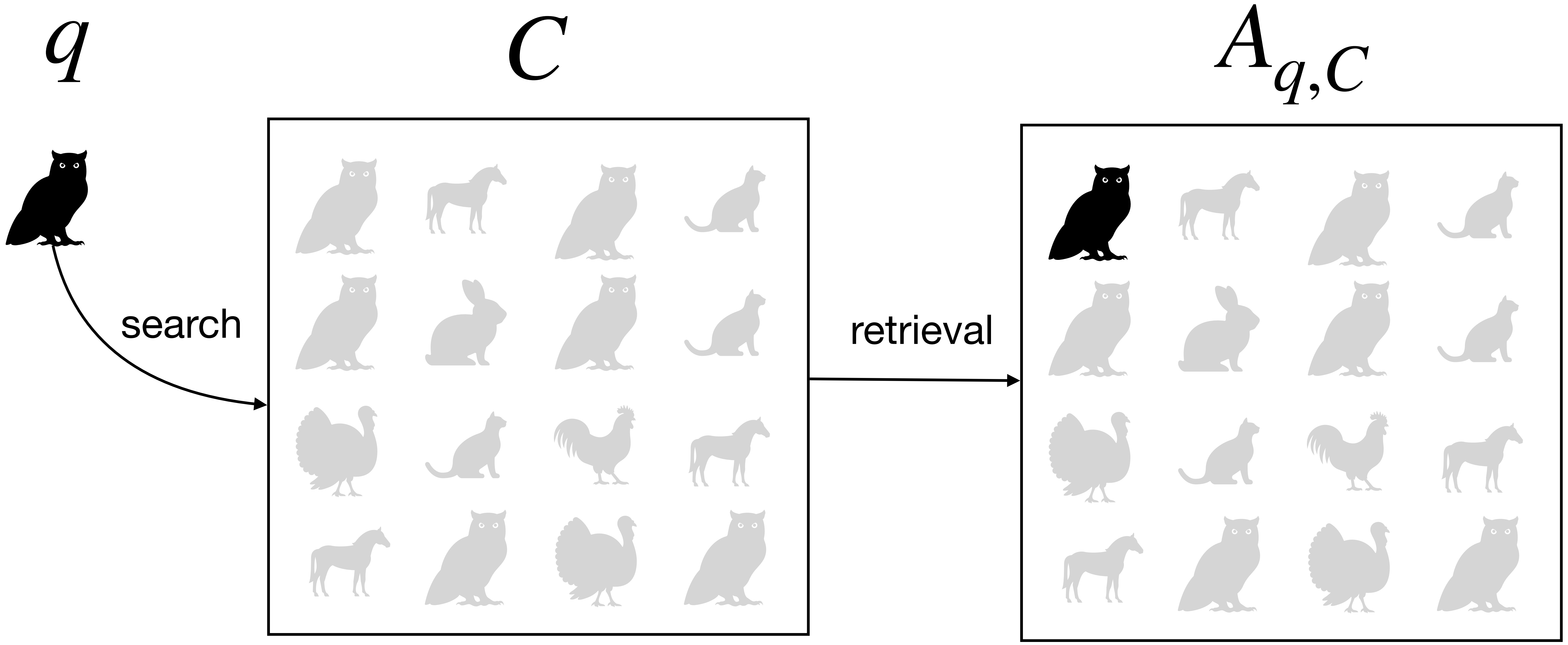
We can measure the quality of our system according to this notion of quality, called **Precision**

$$Prec = \frac{relevant\ retrieved}{retrieved}$$

$$Prec_q = \frac{4}{7} = 0.57$$

Search evaluation: the notion of quality

Question: why **Precision** is a **necessary** but **not sufficient** property of a good search system?



We retrieved only 1 document and it is correct

However, many relevant documents arre missing

$$Prec = \frac{relevant\ retrieved}{retrieved}$$

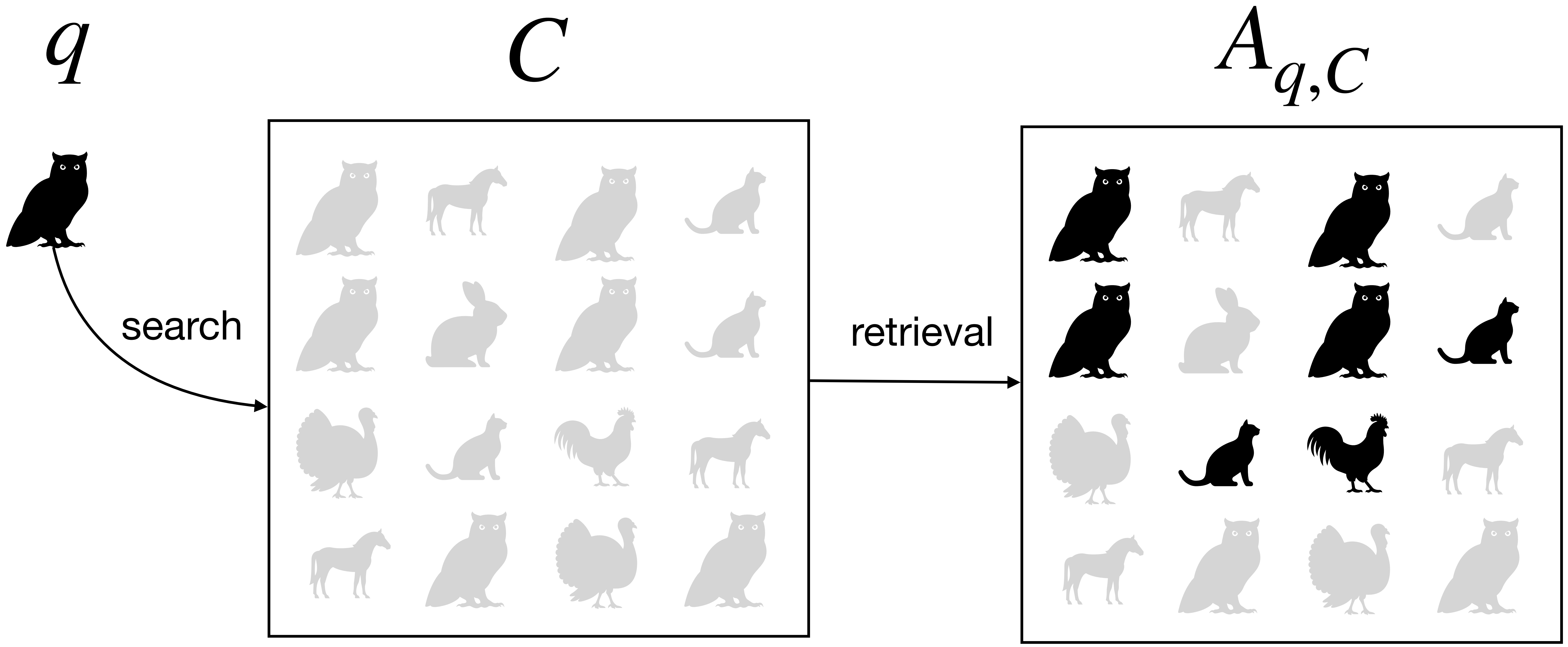
$$Prec_q = \frac{1}{1} = 1$$

Search evaluation: the notion of quality

Question: when we say that the search answers $\boldsymbol{A_{q,C}}$ are good?

Definition 2: *when all the relevant documents contained in **C** are retrieved by **q***

Remember: in order to know if a document is actually relevant, we need a **ground truth** (or a **user feedback**)



We retrieved 4 relevant documents from a corpus which contains 6 relevant documents

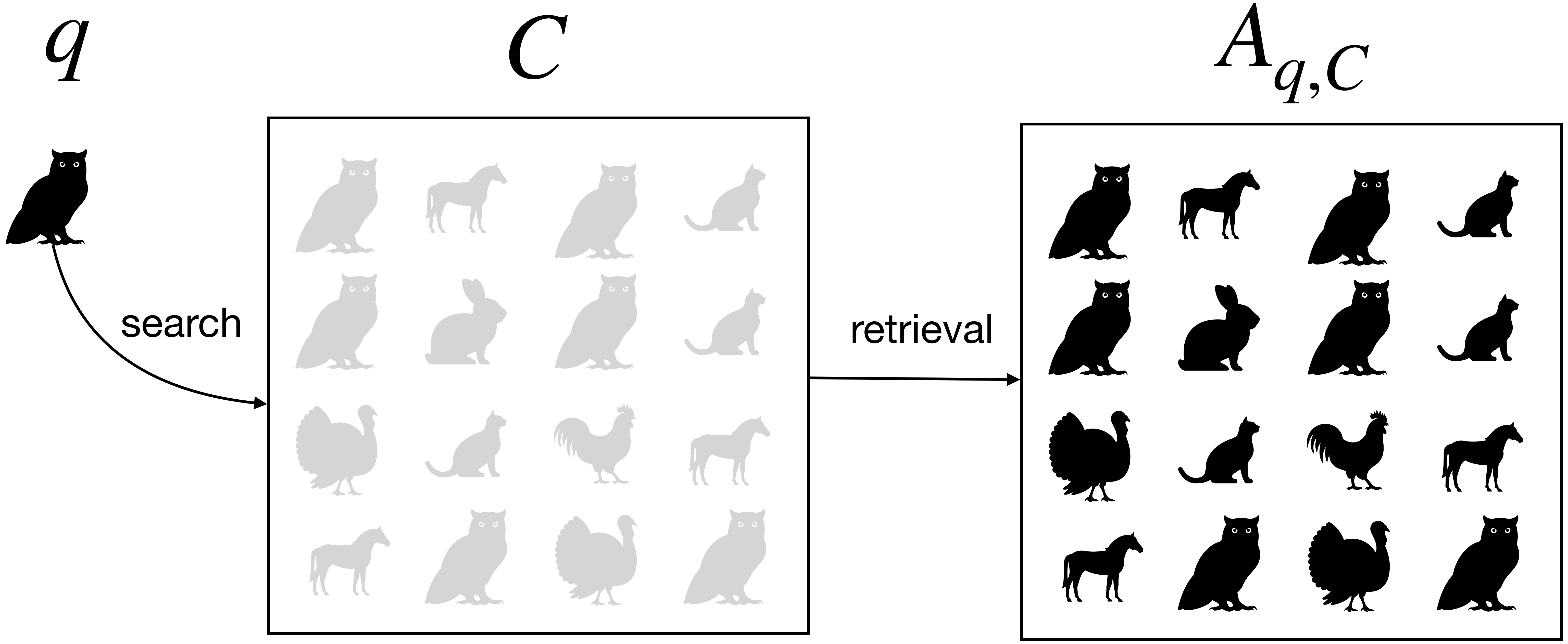
We can measure the quality of our system according to this notion of quality, called **Recall**

$$Rec = \frac{relevant\ retrieved}{relevant}$$

$$Rec_q = \frac{4}{6} = 0.66$$

Search evaluation: the notion of quality

Question: why **Recall** is a **necessary** but **not sufficient** property of a good search system?



We retrieved all the documents and this means to retrieve all the relevant ones by definition

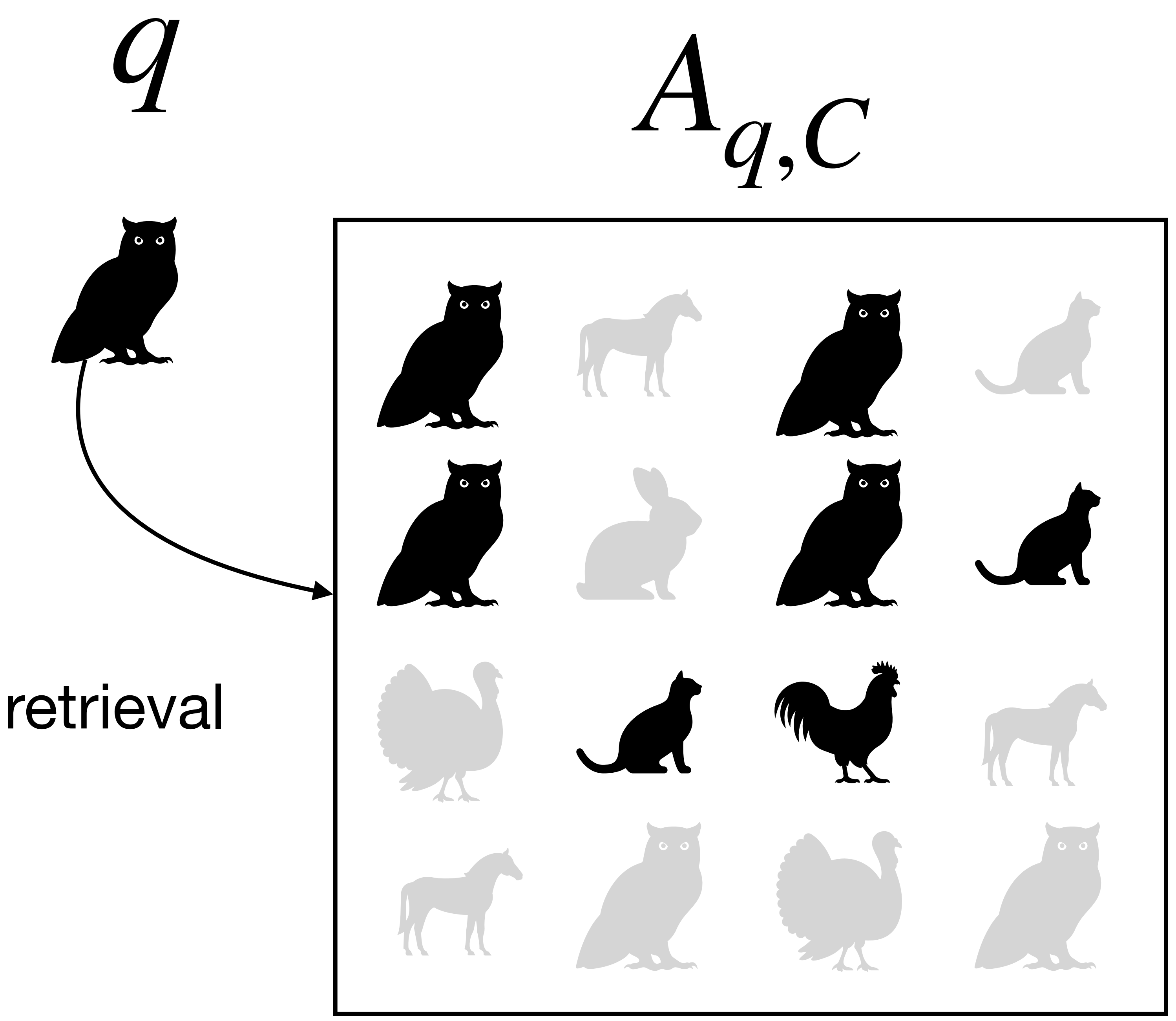
However, there are a lot of wrong results

$$Rec = \frac{relevant\ retrieved}{relevant}$$

$$Rec_q = \frac{6}{6} = 1$$

Search evaluation: the notion of quality

Definition 3: we aim at a system with a good tradeoff between precision and recall; this can be measured by the **f1-score**



$$F1 = \frac{2 \cdot Prec \cdot Rec}{Prec + Rec} = \frac{2 \cdot 0.57 \cdot 0.66}{0.57 + 0.66} = 0.61$$

Question: when the numbers we obtain from these measures are good? Try to perform search by tossing a coin…

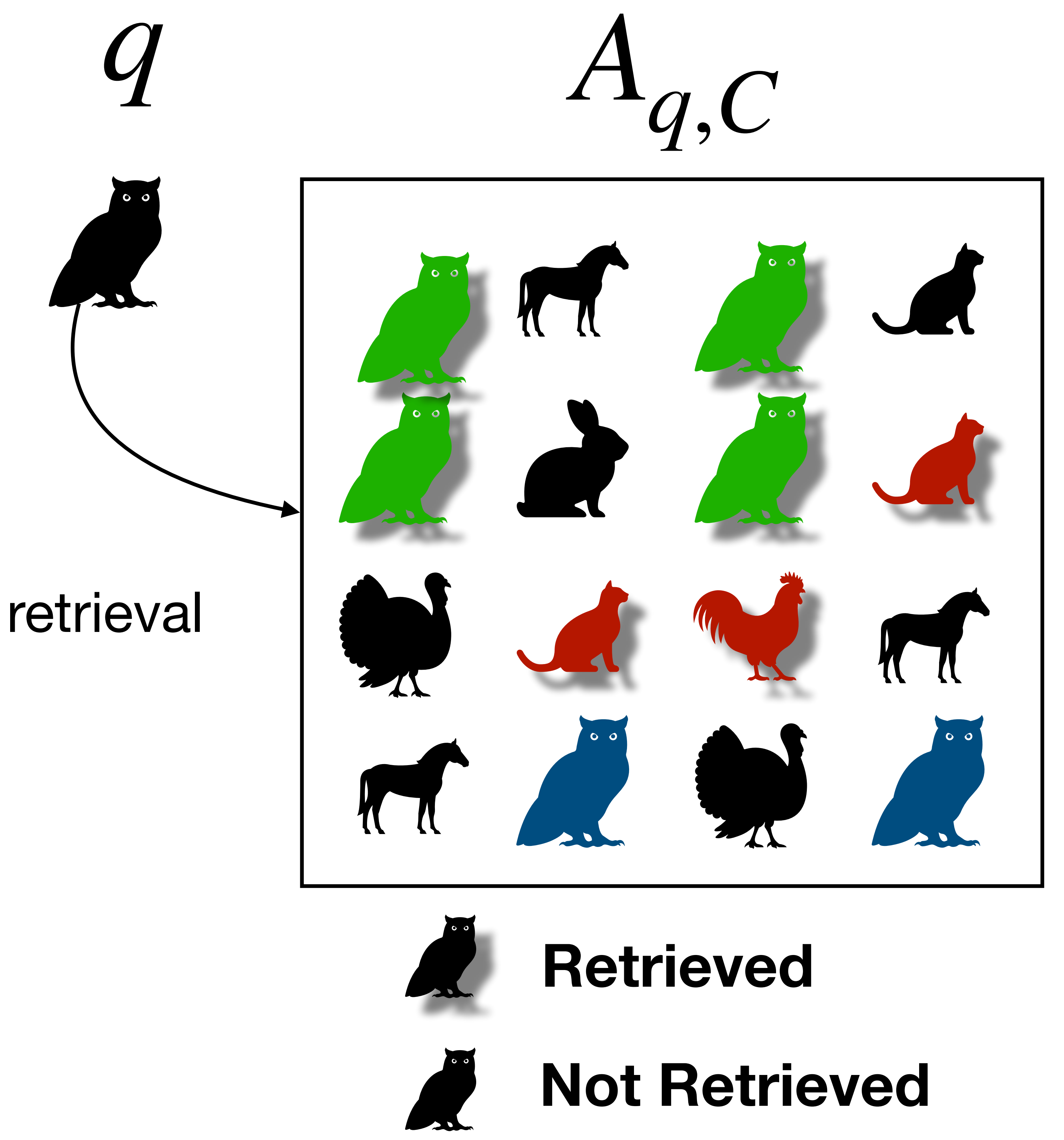
A more formal definition of Precision and Recall

Given a query q and a ground truth providing the set E_q of relevant documents for q, we denote A_q the set of query answers provided by the system under evaluation

For each document d:

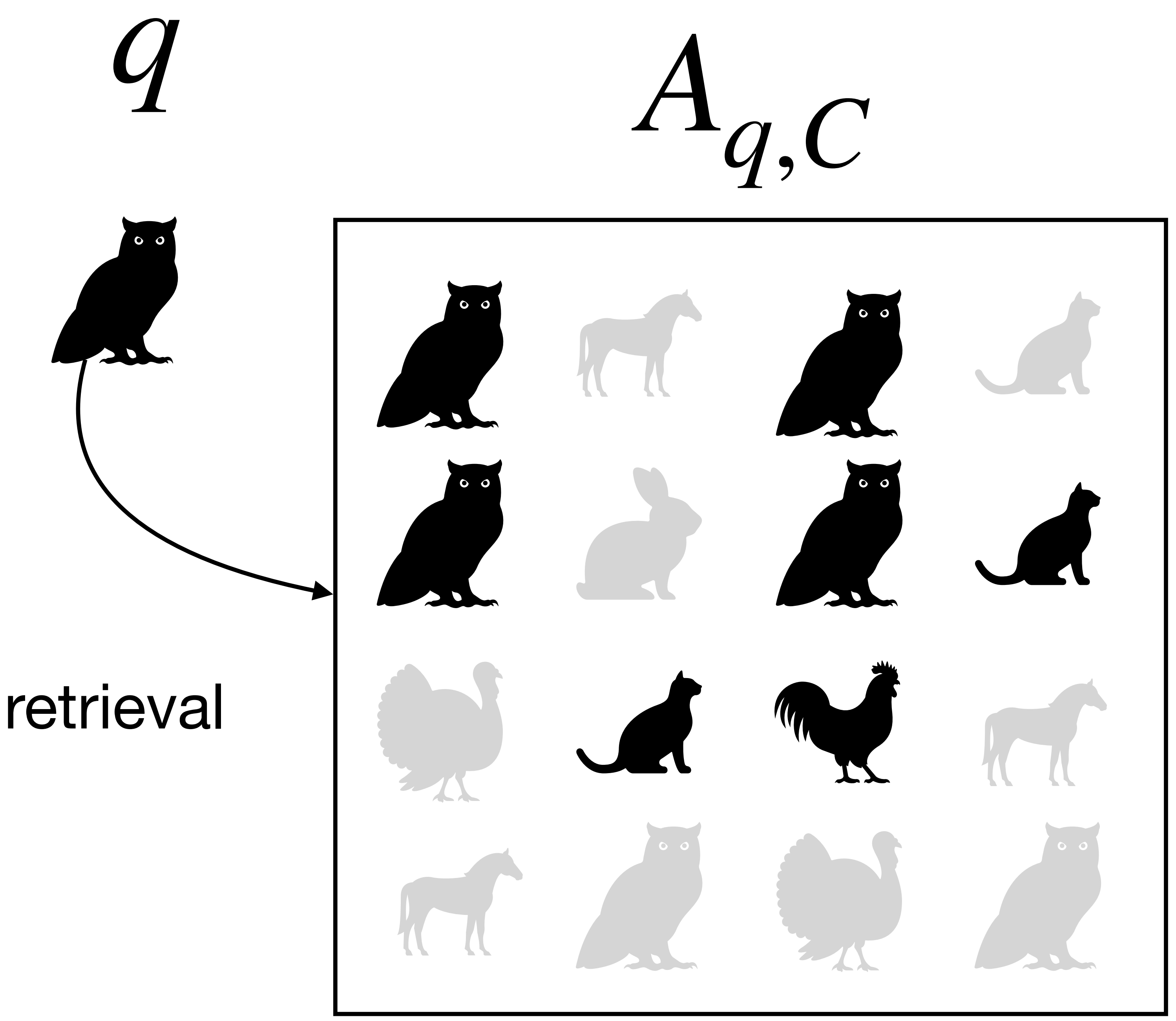
	$d \in E_q$	$d \notin E_q$	
$d \in A_q$	**TP** True Positive	**FP** False Positive	**Retrieved**
$d \notin A_q$	**FN** False Negative	**TN** True Negative	**Not retrieved**
	Relevant	**Not Relevant**	

$$Prec = \frac{TP}{TP + FP};\ \ Rec = \frac{TP}{TP + FN};\ \ F1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$



Confusion Matrix

When evaluating a search system, it is important to understand in which cases we have errors: it is more the r**etrieval of wrong documents (FP)** or instead the fact that we **miss many documents (FN)**



		Ground truth		
	q	$R = 1$	$R = 0$	
Predicted values	$R = 1$	$TP = 4$	$FP = 3$	7
	$R = 0$	$FN = 2$	$TN = 7$	9
		6	10	16

R is the variable that represent the document relevance to the query

Search evaluation: confusion matrix and other measures

specificity	negative predictive value	miss rate	fall-out	false discovery rate	false omission rate	critical success index
$TNR = \frac{TN}{TN + FP}$	$NPV = \frac{TN}{TN + FN}$	$FNR = \frac{FN}{FN + TP}$	$FPR = \frac{FP}{FP + TN}$	$FDR = \frac{FP}{FP + TP}$	$FOR = \frac{FN}{FN + TN}$	$TS = \frac{TP}{TP + FN + FP}$

Prevalence threshold

$$PT = \frac{\sqrt{Rec(1 - TNR)} + TNR - 1}{Rec + TNR - 1}$$

Accuracy

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

Balanced accuracy

$$BA = \frac{Rec + TNR}{2}$$

Informedness

$$BM = Rec + TNR - 1$$

Markedness

$$MK = Prec + NPV - 1$$

Matthews correlation coefficient

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

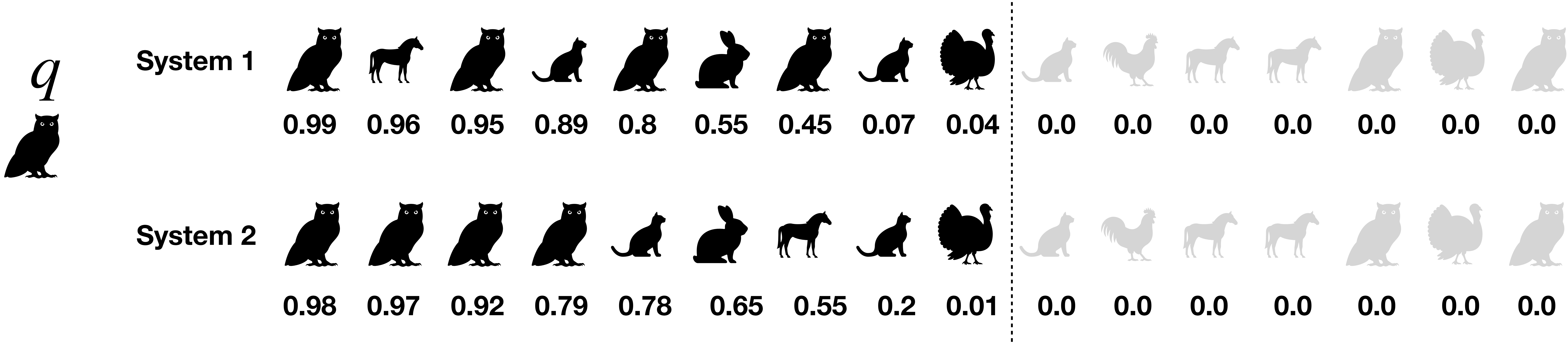
Fowlkes-Mallows index

$$FM = \sqrt{\frac{2TP}{(TP + FP)(TP + FN)}}$$

Quick summary: *https://en.wikipedia.org/wiki/Evaluation_measures_(information_retrieval)*

Evaluation of ranking systems

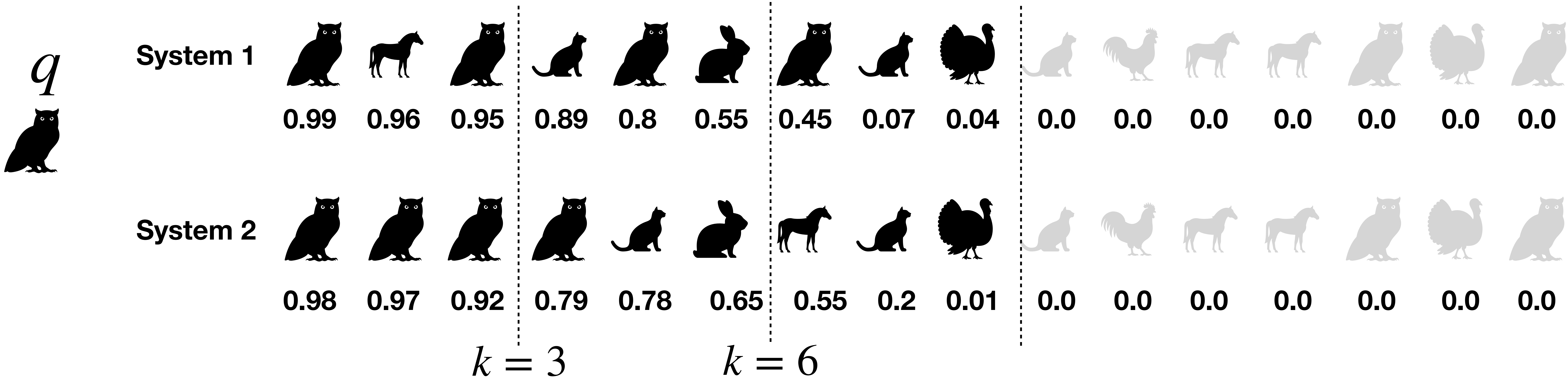
The answer of a non boolean search system is not a set of retrieved documents, rather a rank of documents with a relevance score (that is typically the cosine similarity between the query and the document). **How do we evaluate the system in this case?**



Note that the two systems achieve the **same Precision and Recall.** However, the second system is better.

Evaluation of ranking systems

Solution 1: we could set a threshold too select the top-k results and use them to evaluate precision and recall. But where should we put the threshold?

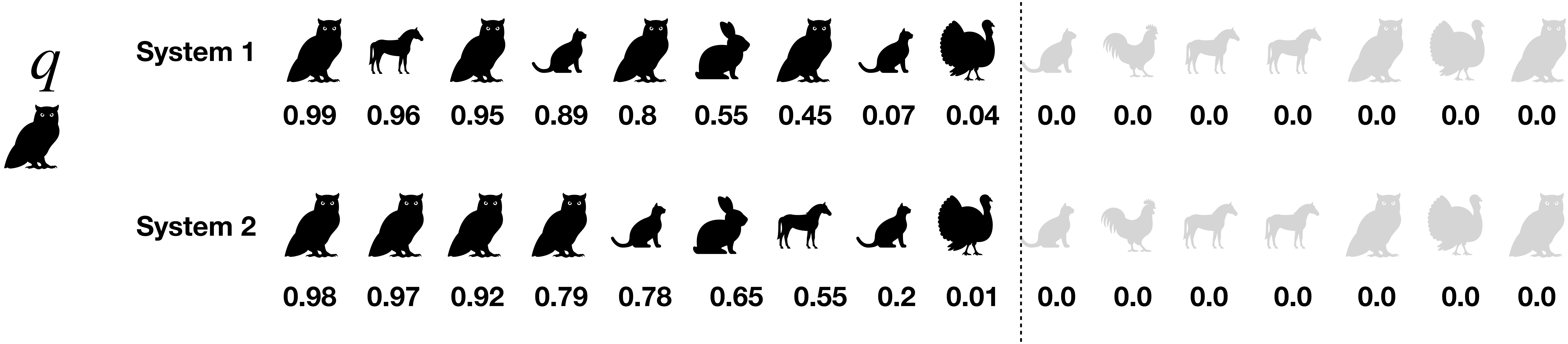


Precision at k **System 1:** $Prec_{k=3} = \frac{2}{3};\ Prec_{k=6} = \frac{1}{2}$ **System 2:** $Prec_{k=3} = 1;\ Prec_{k=6} = \frac{2}{3}$

Still the order of results is not completely taken into account

Evaluation of ranking systems

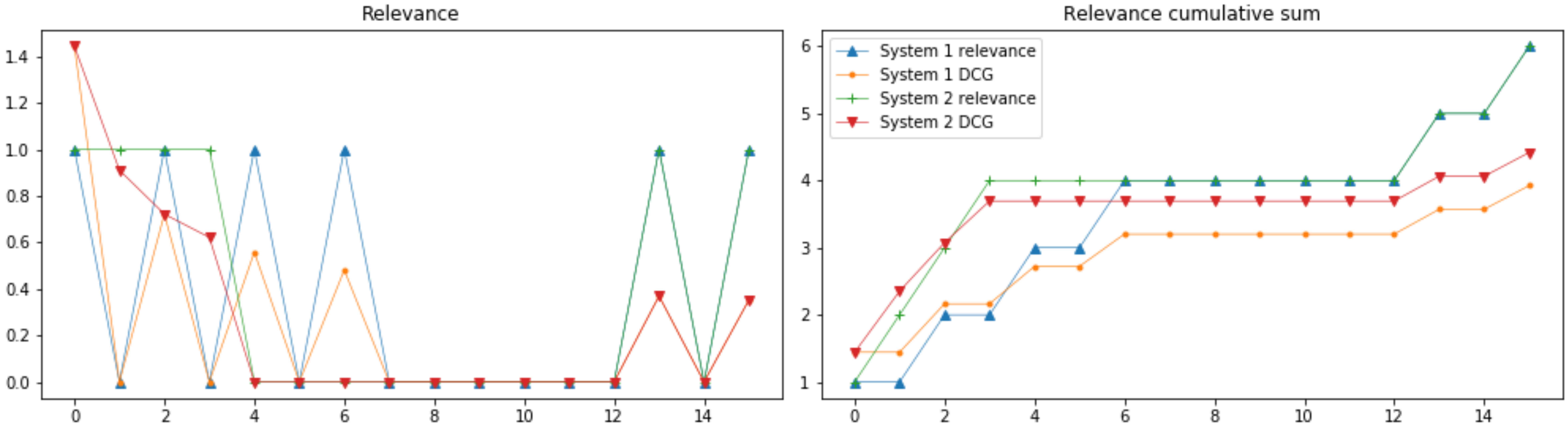
Solution 2: **Discounted cumulative gain**: we discount the relevance of each document according to its position in the ranking



Discounted cumulative gain: $DCG = \sum_{i=1}^{n} \frac{R_i}{\log(i+1)}$

Evaluation of ranking systems

Solution 2: **Discounted cumulative gain**: we discount the relevance of each document according to its position in the ranking

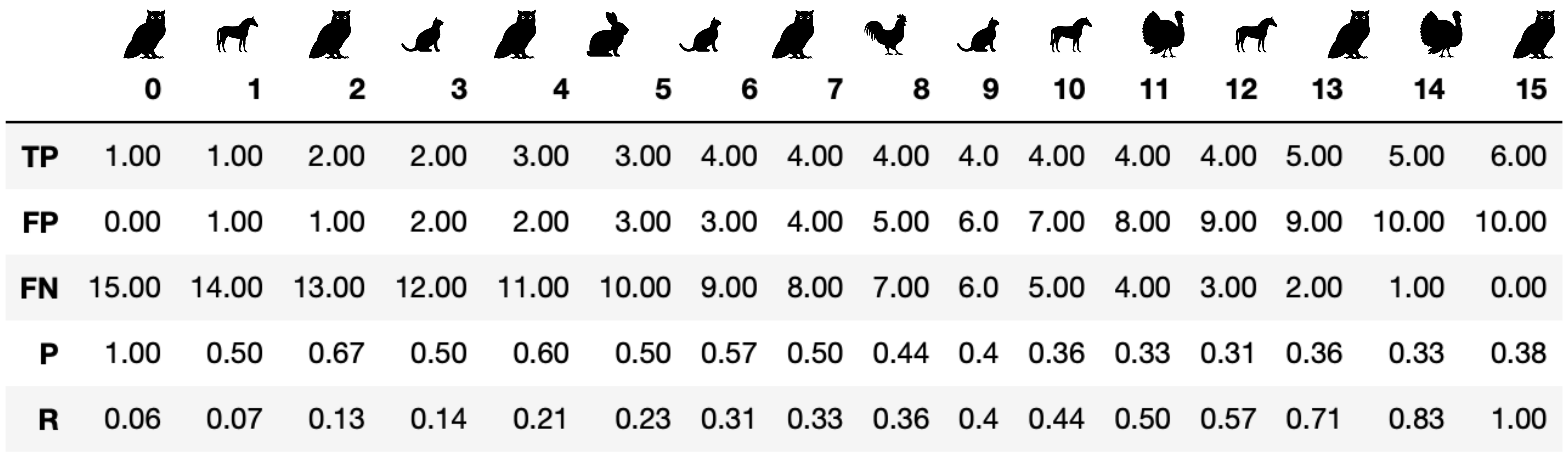


System 1: 3.93 System 2: 4.42

Evaluation of ranking systems

Solution 3: Precision Vs Recall. When moving along the ranking from top to bottom, the **Recall** increases by definition. We can just measure the **Precision** scored for different levels of recall.

System 1



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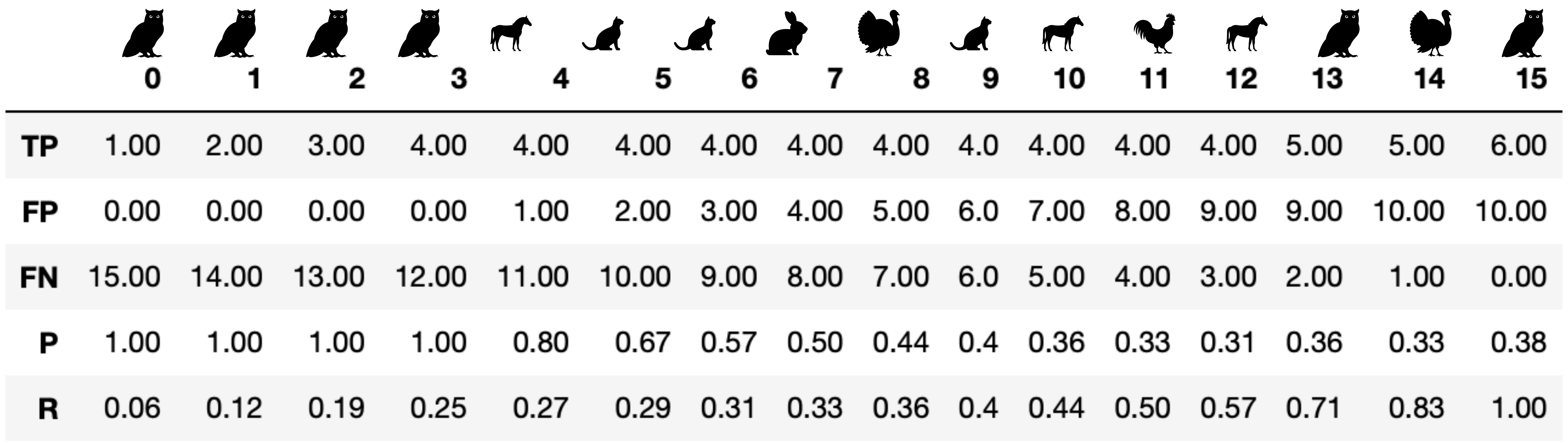
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
TP	1.00	1.00	2.00	2.00	3.00	3.00	4.00	4.00	4.00	4.0	4.00	4.00	4.00	5.00	5.00	6.00
FP	0.00	1.00	1.00	2.00	2.00	3.00	3.00	4.00	5.00	6.0	7.00	8.00	9.00	9.00	10.00	10.00
FN	15.00	14.00	13.00	12.00	11.00	10.00	9.00	8.00	7.00	6.0	5.00	4.00	3.00	2.00	1.00	0.00
P	1.00	0.50	0.67	0.50	0.60	0.50	0.57	0.50	0.44	0.4	0.36	0.33	0.31	0.36	0.33	0.38
R	0.06	0.07	0.13	0.14	0.21	0.23	0.31	0.33	0.36	0.4	0.44	0.50	0.57	0.71	0.83	1.00

System 2



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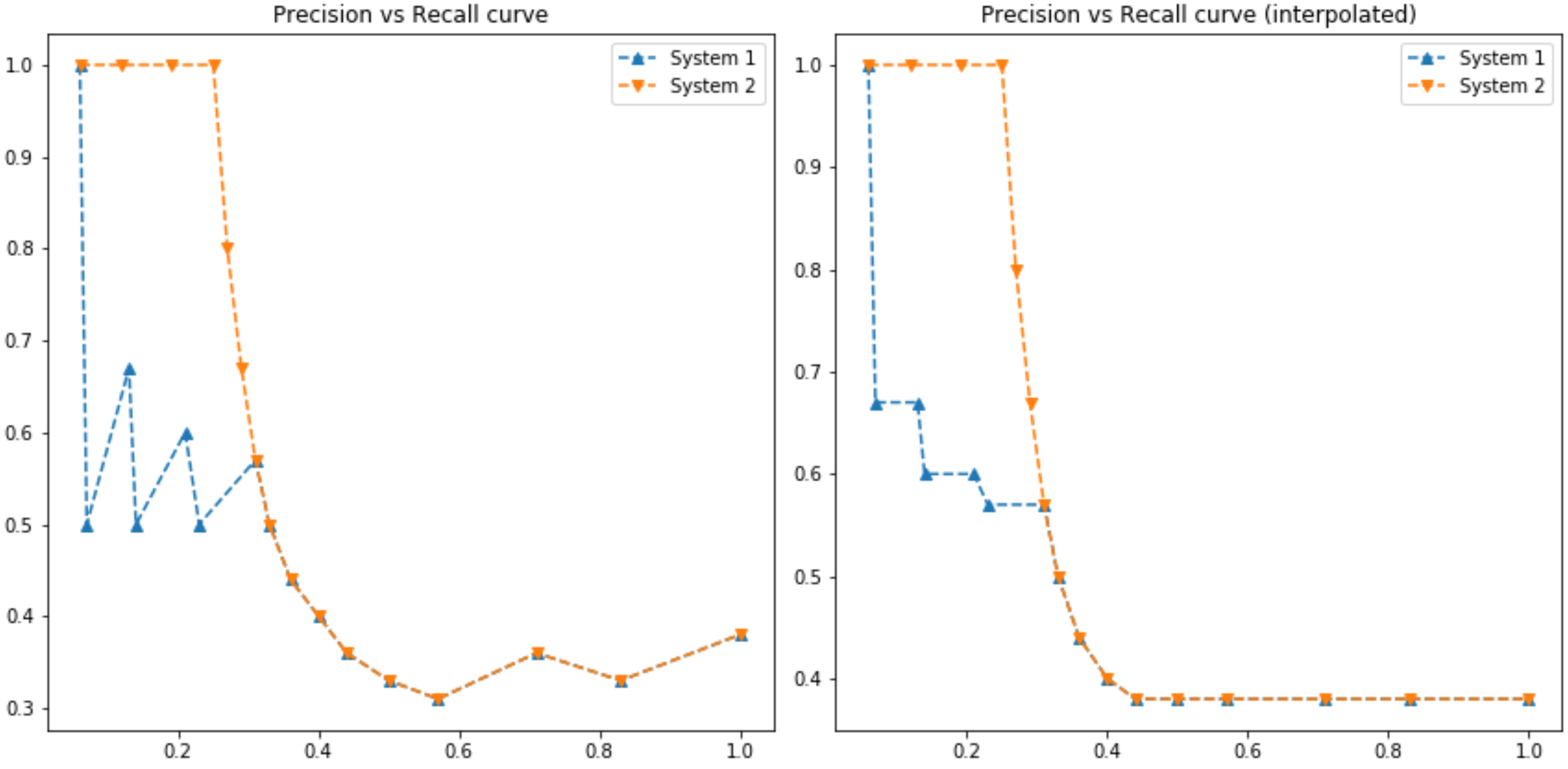
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
TP	1.00	2.00	3.00	4.00	4.00	4.00	4.00	4.00	4.00	4.0	4.00	4.00	4.00	5.00	5.00	6.00
FP	0.00	0.00	0.00	0.00	1.00	2.00	3.00	4.00	5.00	6.0	7.00	8.00	9.00	9.00	10.00	10.00
FN	15.00	14.00	13.00	12.00	11.00	10.00	9.00	8.00	7.00	6.0	5.00	4.00	3.00	2.00	1.00	0.00
P	1.00	1.00	1.00	1.00	0.80	0.67	0.57	0.50	0.44	0.4	0.36	0.33	0.31	0.36	0.33	0.38
R	0.06	0.12	0.19	0.25	0.27	0.29	0.31	0.33	0.36	0.4	0.44	0.50	0.57	0.71	0.83	1.00

Precision vs Recall curve

$AvgP = \int_0^1 P(R)dR \approx \sum_{k=1}^{n} P(k)\Delta R(k)$, **where** $\Delta R(k)$ **is the change in** R **from** $k-1$ **to** k

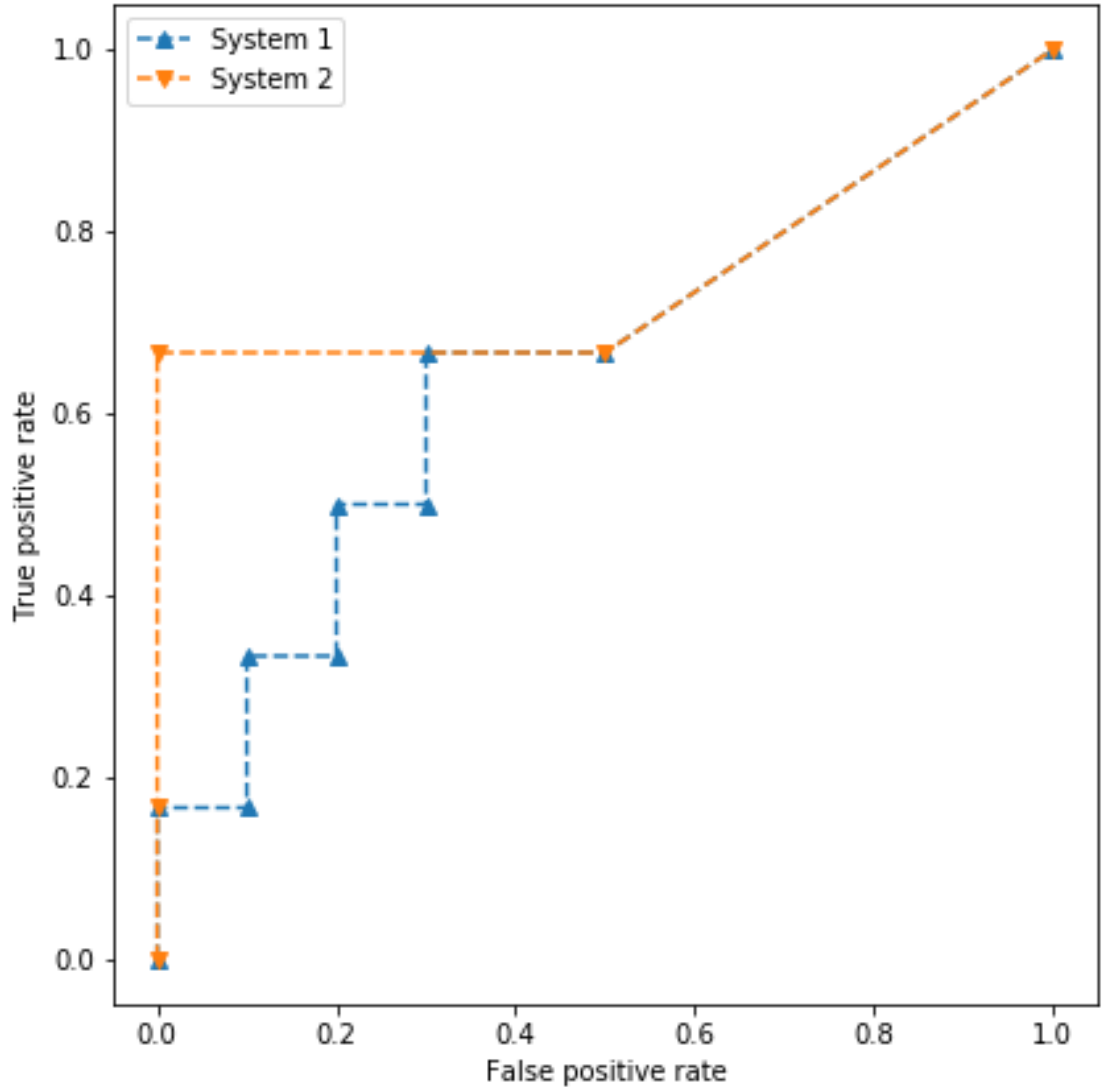


$$Prec_{interpolated}(Rec_i) = \max_{j \geq i} Prec(Rec_j)$$

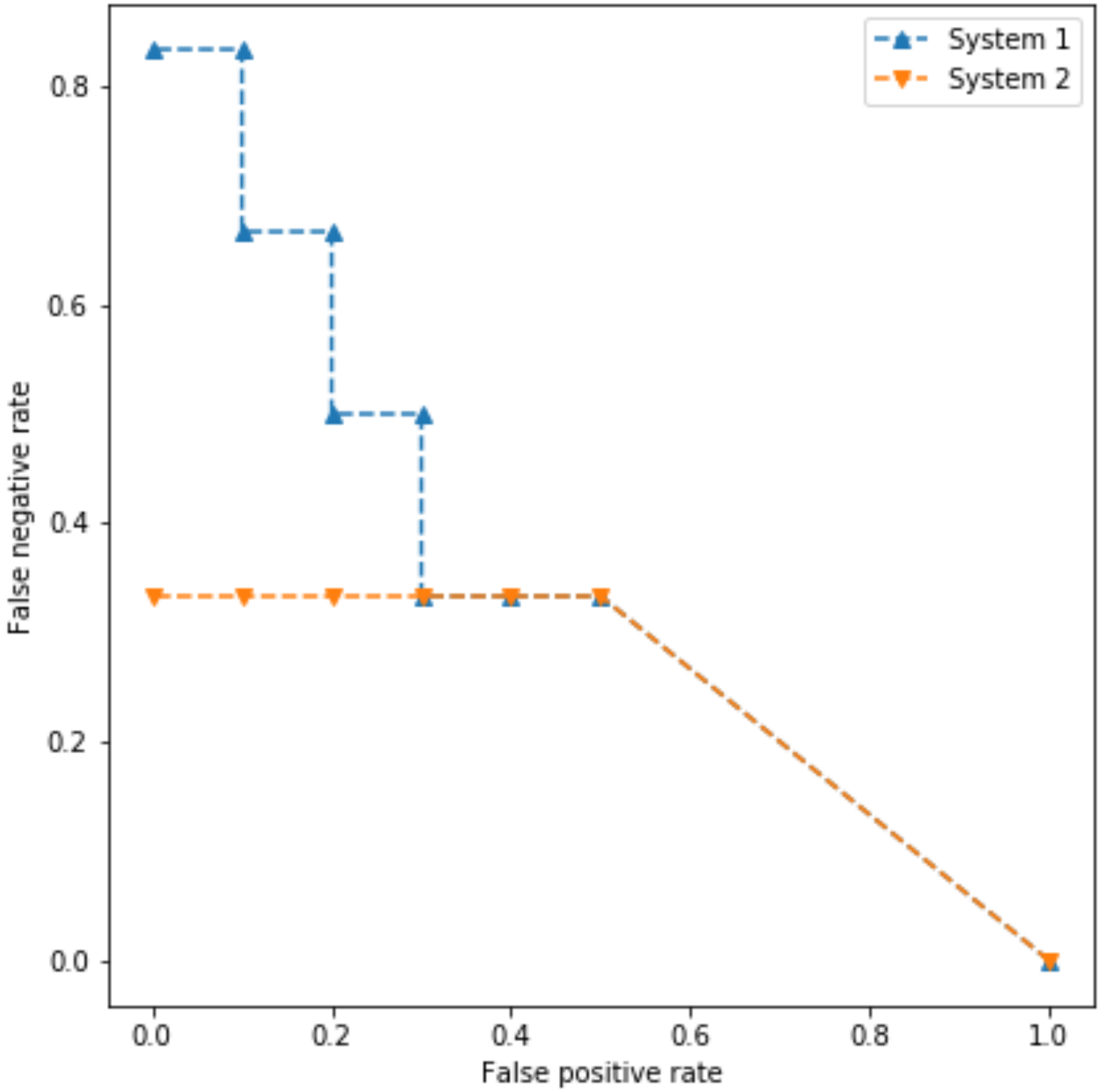
Other curves

The **ROC (receiver operating characteristic)** curve is created by plotting the **true positive rate (TPR) (Recall)** against the **false positive rate (FPR) (FP / (FP + TN))** at various threshold settings.

ROC (receiver operating characteristic)



Detection Error Tradeoff (DET)



The **Detection Error Tradeoff (DET)** curve is created by plotting the **false negative rate (FNR) (FN / (FN + TP)** against the **false positive rate (FPR) (FP / (FP + TN))** at various threshold settings.