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Datasets of the Unsupervised and Transfer Learning Challenge

Report prepared by Isabelle Guyon with information from the data donors listed below:

Handwriting recognition (AVICENNA) – Reza Farrahi Moghaddam, Mathias Adankon, Kostyantyn Filonenko, Robert Wisnovsky, and Mohamed Chériet (Ecole de technologie supérieure de Montréal, Quebec) contributed the dataset of Arabic manuscripts.

Human action recognition (HARRY) – Ivan Laptev and Barbara Caputo collected and made publicly available the KTH human action recognition datasets. Marcin Marszałek, Ivan Laptev and Cordelia Schmid collected and made publicly available the Hollywood 2 dataset of human actions and scenes.

Object recognition (RITA) – Antonio Torralba, Rob Fergus, and William T. Freeman, collected and made available publicly the 80 million tiny image dataset. Vinod Nair and Geoffrey Hinton collected and made available publicly the CIFAR datasets. See the techreport Learning Multiple Layers of Features from Tiny Images, by Alex Krizhevsky, 2009, for details.

Ecology (SYLVESTER) – Jock A. Blackard, Denis J. Dean, and Charles W. Anderson of the US Forest Service, USA, collected and made available the (Forest cover type) dataset.

Text processing (TERRY) – David Lewis formatted and made publicly available the RCV1-v2 Text Categorization Test Collection derived from REUTER news clips.

The toy example (ULE) is the MNIST handwritten digit database made available by Yann LeCun and Corinna Costes.

1. Data formats

All the data sets are in the same format; xxx should be replaced by one of:

devel: development data

valid: evaluation data used as validation set

final: final evaluation data

The participants have access only to the files outlined in red:

dataname.param: Parameters and statistics about the data

Table 1: Datasets of the unsupervised and transfer learning challenge.

Dataset	Domain	Feat. num.	Sparsity (%)	Development num.	Transfer num.	Validation num.	Final Eval. num.	Data (text)	Data (Matlab)
AVICENNA	Arabic manuscripts	120	0.00	150205	50000	4096	4096	16 MB	14 MB
HARRY	Human action recognition	5000	98.12	69652	20000	4096	4096	13 MB	15 MB
RITA	Object recognition	7200	1.19	111808	24000	4096	4096	1026 MB	762 MB
SYLVESTER	Ecology	100	0.00	572820	100000	4096	4096	81 MB	69 MB
TERRY	Text recognition	47236	99.84	217034	40000	4096	4096	73 MB	56 MB
ULE (toy data)	Handwritten digits	784	80.85	26808	10000	4096	4096	7 MB	13 MB

dataname_xxx.data: Unlabeled data (a matrix of space delimited numbers, patterns in lines, features in columns).

dataname_xxx.mat: The same data matrix in Matlab format in a matrix called X_xxx.

dataname_transfer.label: Target values provided for transfer learning only. Multiple labels (1 per column), label values are -1, 0, or 1 (for negative class, unknown, positive class).

dataname_valid.label: Target values, not provided to participants.

dataname_final.label: Target values, not provided to participants.

dataname_xxx.dataid: Identity of the samples (lines of the data matrix).

dataname_xxx.labelid: Identity of the labels (variables that are target values, i.e., columns of the label matrix.)

dataname.classid: strings representing the names of the classes.

The participants will use the following formats results:

dataname_valid.prepro: Preprocessed data send during the development phase.

dataname_final.prepro: Preprocessed data for the final submission.

2. Metrics

The data representations are assessed automatically by the evaluation platform. To each evaluation set (validation set or final evaluation set) the organizers have assigned several binary classification tasks unknown to the participants. The platform will use the data representations provided by the participants to train a linear classifier (code provided in Appendix) to solve these tasks.

To that end, the evaluation data (validation set or final evaluation set) are partitioned randomly into a training set and a test set. The parameters of the linear classifier are adjusted using the training set. Then, predictions are made on test data using the trained model. The **Area Under the ROC curve** (AUC) is computed to assess the performance of the linear classifier. The results are averaged over all tasks and over several random splits into a training set and a complementary test set.

The number of training examples is varied and the AUC is plotted against the number of training examples in a log scale (to emphasize the results on small numbers of training examples). The area under the learning curve (ALC) is used as scoring metric to synthesize the results.

The participants are ranked by ALC for each individual dataset. The participants having submitted a **complete experiment** (results on all 5 datasets of the challenge) enter the final ranking. The winner is determined by the best average rank over all datasets for the results of their last complete experiment.

2.1. Global Score: The Area under the Learning Curve (ALC)

The prediction performance is evaluated according to the Area under the Learning Curve (ALC). A learning curve plots the **Area Under the ROC curve** (AUC) averaged over all the binary classification tasks and all evaluation data splits. The AUC is the area of the curve that plots the sensitivity (error rate of the "positive class") vs. the specificity (error rate of the "negative" class).

We consider two baseline learning curves:

1. The ideal learning curve, obtained when perfect predictions are made (AUC=1). It goes up vertically then follows AUC=1 horizontally. It has the maximum area "Amax".

2. The "lazy" learning curve, obtained by making random predictions (expected value of AUC: 0.5). It follows a straight horizontal line. We call its area "Arand".

To obtain our ranking score displayed in Mylab and on the Leaderboard, we normalize the ALC as follows:

$$\text{global\_score} = (\text{ALC} - \text{Arand})/(\text{Amax} - \text{Arand})$$

For simplicity, we call ALC the normalized ALC or global score.

We show in Figure 3 examples of learning curves for the toy example ULE, obtained using the sample code. Note that we interpolate linearly between points. The global score depends on how we scale the x-axis. We use a log2 scaling for all datasets.

3. A – ULE

This dataset is not part of the challenge. It is given as an example, for illustration purpose, together with ALL the labels.

3.1. Topic

The task of ULE is handwritten digit recognition.

3.2. Sources

3.2.1. Original owners

The data set was constructed from the MNIST data that is made available by Yann LeCun of the NEC Research Institute at http://yann.lecun.com/exdb/mnist/.

The digits have been size-normalized and centered in a fixed-size image of dimension 28×28. We show examples of digits in Figure 1.

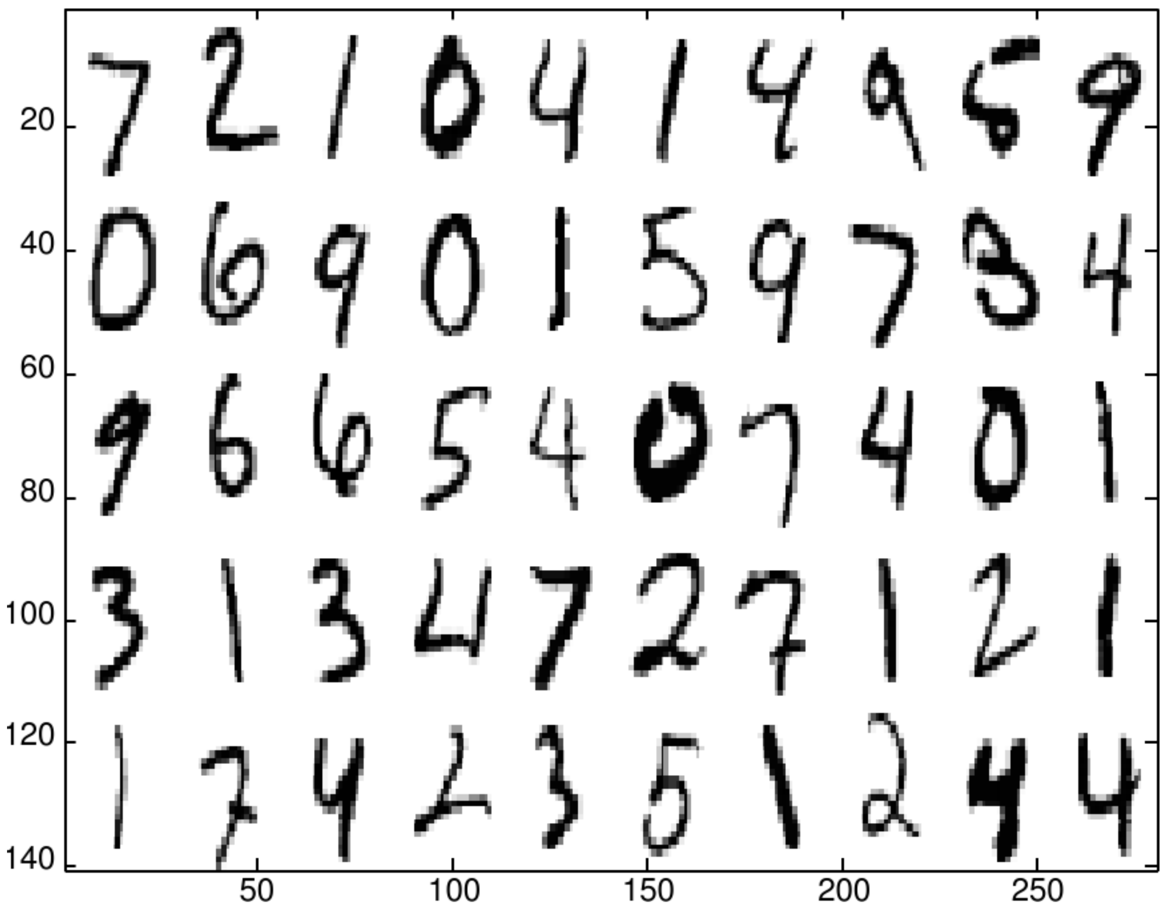


Figure 1: Examples of digits from the MNIST database.

3.2.2. Donor of database

This version of the database was prepared for the "unsupervised and transfer learning challenge" by Isabelle Guyon, 955 Creston Road, Berkeley, CA 94708, USA (isabelle@clopinet.com).

Table 2: Number of examples in the original data

Digit	0	1	2	3	4	5	6	7	8	9	Total
Training	5923	6742	5958	6131	5842	5421	5918	6265	5851	5949	60000
Test	980	1135	1032	1010	982	892	958	1028	974	1009	10000
Total	6903	7877	6990	7141	6824	6313	6876	7293	6825	6958	70000

3.2.3. Date prepared for the challenge

November 2010.

3.3. Past usage

Many methods have been tried on the MNIST database, in its original data split (60,000 training examples, 10,000 test examples, 10 classes.) Table 3 is an abbreviated list from http://yann.lecun.com/exdb/mnist/:

This dataset was used in the NIPS 2003 Feature Selection Challenge under the name GISETTE and in the WCCI 2006 Performance Prediction Challenge and the IJCNN 2007 Agnostic Learning vs. Prior Knowledge Challenge under the name GINA.

References

Gradient-based learning applied to document recognition. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. In *Proceedings of the IEEE*, 86(11):2278–2324, November 1998.

Result Analysis of the NIPS 2003 Feature Selection Challenge. Isabelle Guyon, Asa Ben Hur, Steve Gunn, Gideon Dror, Advances in Neural Information Processing Systems 17, MIT Press, 2004.

Agnostic Learning vs. Prior Knowledge Challenge. Isabelle Guyon, Amir Saffari, Gideon Dror, and Gavin Cawley. In *Proceedings IJCNN 2007*, Orlando, Florida, August 2007.

Analysis of the IJCNN 2007 Agnostic Learning vs. Prior Knowledge Challenge. Isabelle Guyon, Amir Saffari, Gideon Dror, and Gavin Cawley, Neural Network special anniversary issue, in press. [Earlier draft]

Hand on Pattern Recognition, challenges in data representation, model selection, and performance prediction. Book in preparation. Isabelle Guyon, Gavin Cawley, Gideon Dror, and Amir Saffari Editors.

3.4. Experimental design

We used the raw data:

- The feature names are the (i, j) matrix coordinates of the pixels (in a 28×28 matrix.)

Table 3: Previous results for MNIST (ULE)

METHOD	TEST ERROR RATE (%)
linear classifier (1-layer NN)	12.0
linear classifier (1-layer NN) [deskewing]	8.4
pairwise linear classifier	7.6
K-nearest-neighbors, Euclidean	5.0
K-nearest-neighbors, Euclidean, deskewed	2.4
40 PCA + quadratic classifier	3.3
1000 RBF + linear classifier	3.6
K-NN, Tangent Distance, 16x16	1.1
SVM deg 4 polynomial	1.1
Reduced Set SVM deg 5 polynomial	1.0
Virtual SVM deg 9 poly [distortions]	0.8
2-layer NN, 300 hidden units	4.7
2-layer NN, 300 HU, [distortions]	3.6
2-layer NN, 300 HU, [deskewing]	1.6
2-layer NN, 1000 hidden units	4.5
2-layer NN, 1000 HU, [distortions]	3.8
3-layer NN, 300+100 hidden units	3.05
3-layer NN, 300+100 HU [distortions]	2.5
3-layer NN, 500+150 hidden units	2.95
3-layer NN, 500+150 HU [distortions]	2.45
LeNet-1 [with 16x16 input]	1.7
LeNet-4	1.1
LeNet-4 with K-NN instead of last layer	1.1
LeNet-4 with local learning instead of ll	1.1
LeNet-5, [no distortions]	0.95
LeNet-5, [huge distortions]	0.85
LeNet-5, [distortions]	0.8
Boosted LeNet-4, [distortions]	0.7
K-NN, shape context matching	0.67

- The data have gray level values between 0 and 255.
- The validation set and the final test set have approximately even numbers of examples for each class.

3.5. Number of examples and class distribution

Table 4: Data statistics for ULE

Dataset	**Domain**	**Feat. num.**	**Sparsity (%)**	**Development num.**	**Transfer num.**	**Validation num.**	**Final Eval. num.**
ULE	Handwriting	784	80.85	26808	10000	4096	4096

All variables are numeric (no categorical variable). There are no missing values. The target variables are categorical. Here is class label composition of the data subsets:

Validation set: `X[4096, 784] Y[4096, 1]`

```
One:    1370
Three:  1372
Seven:  1354
```

Final set: `X[4096, 784] Y[4096, 1]`

```
Zero:   1376
Two:    1373
Six:    1347
```

Development set: `X[26808, 784] Y[26808, 1]`

```
Zero:   2047
One:    2556
Two:    2089
Three:  2198
Four:   3426
Five:   3179
Six:    2081
Seven:  2314
Eight:  3470
Nine:   3448
```

Transfer labels (10000 labels):

```
Four:    2562
Five:    2301
Eight:   2564
Nine:    2573
```

3.6. Type of input variables and variable statistics

The variables in raw data are pixels. We also produced baseline results using as variables Gaussian RBF values with 20 cluster centers generated by the Kmeans clustering algorithm. The algorithm was run on the validation set and the final evaluation set separately. The development set and the transfer labels were not used. The cluster centers are shown in Figure 2.

3.7. Baseline results

We used a linear classifier making independence assumptions between variables, similar to Naïve Bayes, to generate baseline learning curves from raw data and preprocessed data. The normalized ALC (score used in the challenge) are shown in Figures 3 and 4 and summarized in Table 5.

Table 5: Baseline results (normalized ALC for 64 training examples).

ULE	Valid	Final
Raw	0.7905	0.7169
Preprocessed	0.8416	0.3873

4. B – AVICENNA

4.1. Topic

The AVICENNA dataset provides a feature representation of Arabic Historical Manuscripts.

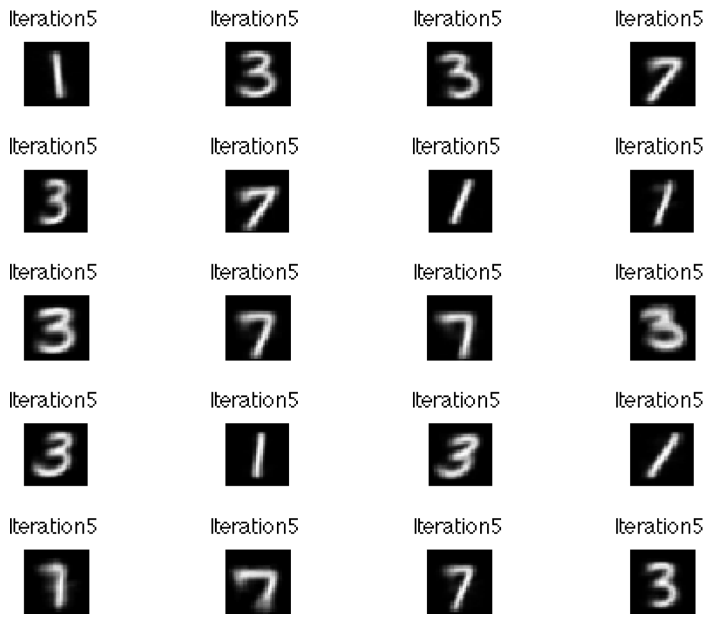
4.2. Sources

4.2.1. Original owners

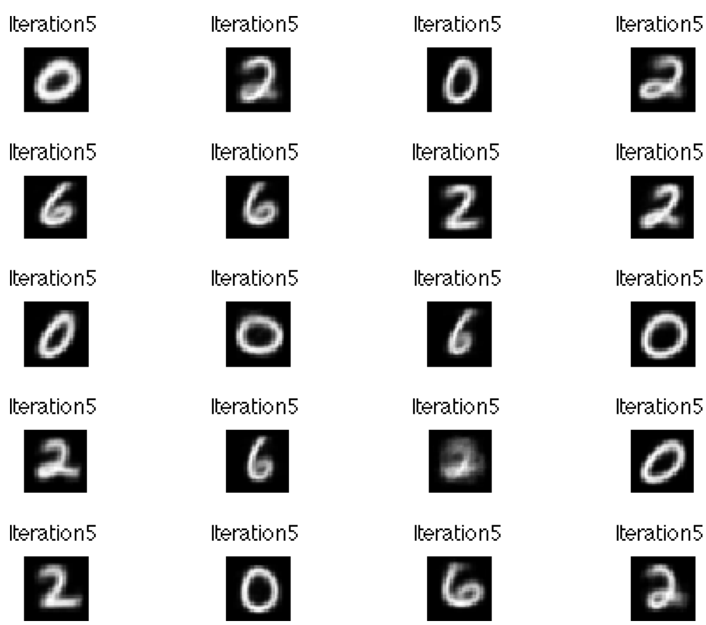
The dataset is prepared on manuscript images provided by The Institute of Islamic Studies (IIS), McGill.

Manuscript author: Abu al-Hasan Ali ibn Abi Ali ibn Muhammad al-Amidi (d. 1243 or 1233)

Manuscript title: Kitab Kashf al-tamwihat fi sharh al-Tanbīhāt (Commentary on Ibn Sina's al-Isharat wa-al-tanbihat)

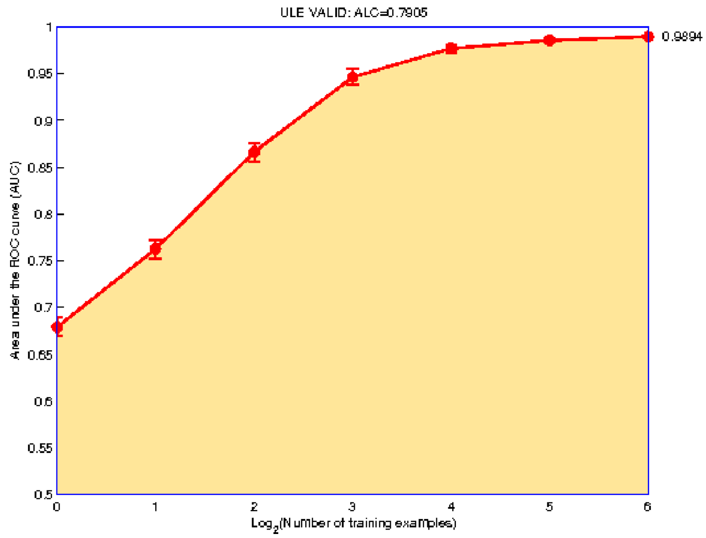


(a) Validation set cluster centers

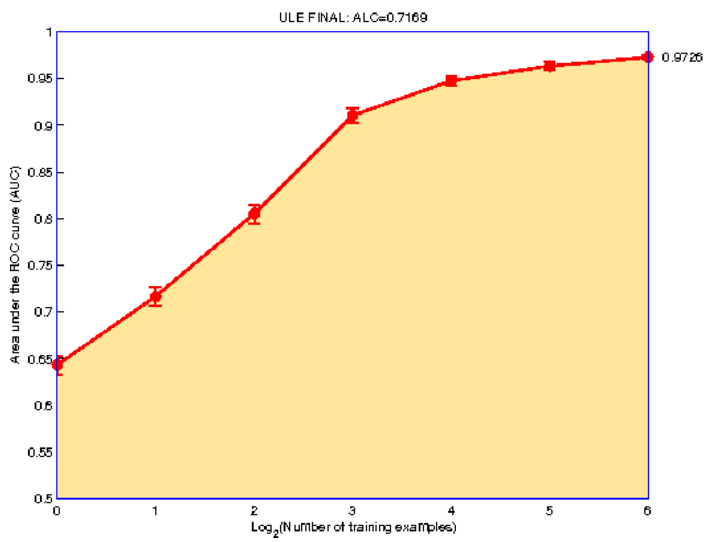


(b) Final evaluation set cluster centers

Figure 2: Clusters obtained by Kmeans clustering

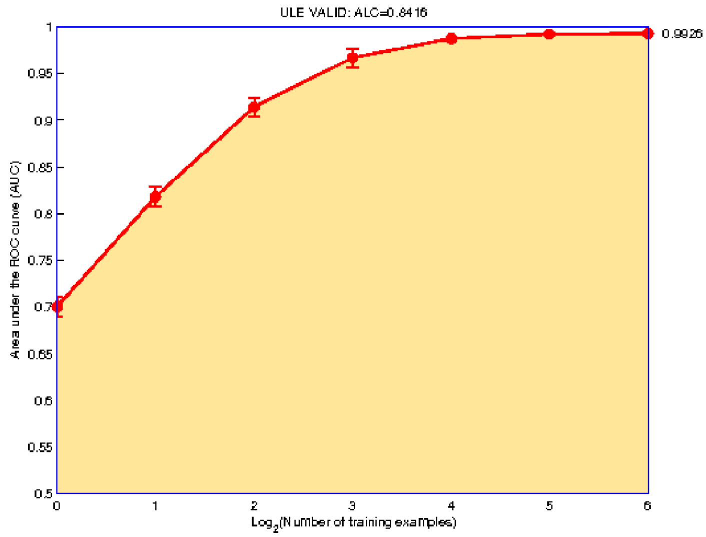


(a)

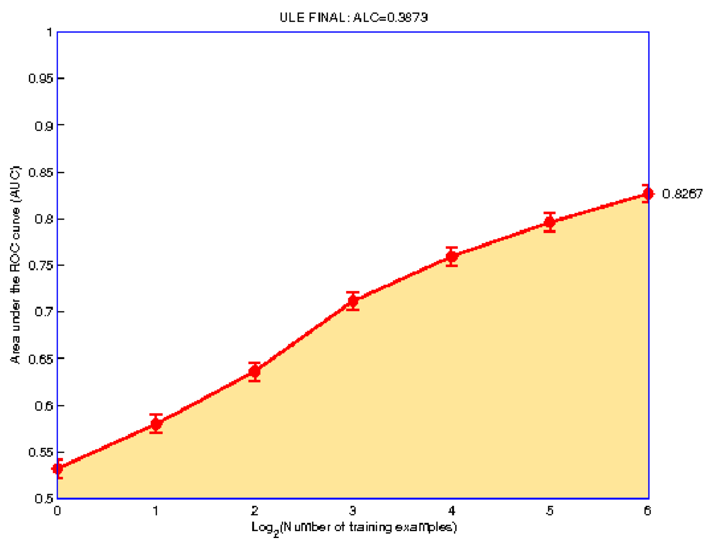


(b)

Figure 3: Baseline results on raw ULE data. Top: validation set. Bottom: final evaluation set.



(a)



(b)

Figure 4: Baseline results on preprocessed ULE data. Top: validation set. Bottom: final evaluation set.

Brief description: Among the works of Avicenna, his *al-Isharat wa-al-tanbihat* received the attention of the later scholars more than others. The reception of this work is particularly intensive and widespread in the period between the late twelfth century to the first half of the fourteenth century, when more than a dozen comprehensive commentaries on this work were composed. These commentaries were one of the main ways of approaching, understanding and developing Avicenna's philosophy and therefore any study of Post-Avicennian philosophy needs to pay specific attention to this commentary tradition. *Kashf al-tamwihat fi sharh al-Tanbihat* by Abu al-Hasan Ali ibn Abi Ali ibn Muhammad al-Amidi (d. 1243 or 1233), one of the early commentaries written on *al-Isharat wa-al-tanbihat*, is an unpublished commentary which still await scholars' attention.

4.2.2. Donors of the database

Reza Farrahi Moghaddam, Mathias Adankon, Kostyantyn Filonenko, Robert Wisnovsky, and Mohamed Cheriet.

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Fax: +1(514)396-8595

4.2.3. Date received:

December 2010

4.3. Past usage:

Part of the data was used in the active learning challenge (http://clopinet.com/al).

4.4. Experimental design

The features were extracted following the procedure described in the JMLR W&CP paper: IBN SINA: A database for handwritten Arabic manuscripts understanding research, by Reza Farrahi Moghaddam, Mathias Adankon, Kostyantyn Filonenko, Robert Wisnovsky, and Mohamed Chériet. The original data includes 92 numeric features. We added 28 distracters then rotated the feature space with a random rotation matrix. Finally, the features were quantized and rescaled between 0 and 999.

4.5. Data statistics

Table 6: Data statistics for AVICENNA.

Dataset	**Domain**	**Feat. num.**	**Sparsity (%)**	**Development num.**	**Transfer num.**	**Validation num.**	**Final Eval. num.**
AVICENNA	Arabic manuscripts	120	0	150205	50000	4096	4096

Table 7: Original feature statistics

Name	**Type**	**Min**	**Max**	**Num val**
Aspect_ratio	continuous	0	999	395
Horizontal_frequency	ordinal	1	13	13
Vertical_CM_ratio	continuous	0	999	539
Singular_points	continuous	0	238	51
Height_ratio	continuous	0	999	163
Hole_feature	binary	0	1	2
End_points	continuous	0	72	43
Dot_feature	binary	0	1	2
BP_hole_1	binary	0	1	2
BP_EP_1	binary	0	1	2
BP_BP_1	binary	0	1	2
BP_hole_2	binary	0	1	2
BP_EP_2	binary	0	1	2
BP_BP_2	binary	0	1	2
BP_hole_3	binary	0	1	2
BP_EP_3	binary	0	1	2
BP_BP_3	binary	0	1	2
BP_hole_4	binary	0	1	2
BP_EP_4	binary	0	1	2
BP_BP_4	binary	0	1	2
BP_hole_5	binary	0	1	2
BP_EP_5	binary	0	1	2
BP_BP_5	binary	0	1	2
BP_hole_6	binary	0	1	2
BP_EP_6	binary	0	1	2
BP_BP_6	binary	0	1	2
EP_BP_1	binary	0	1	2
EP_EP_1	binary	0	1	2
EP_VCM_1	ordinal	0	2	3
EP_BP_2	binary	0	1	2
EP_EP_2	binary	0	1	2

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Name	Type	Min	Max	Num val
EP_VCM_2	ordinal	0	2	3
EP_BP_3	binary	0	1	2
EP_EP_3	binary	0	1	2
EP_VCM_3	ordinal	0	2	3
EP_BP_4	binary	0	1	2
EP_EP_4	binary	0	1	2
EP_VCM_4	ordinal	0	2	3
EP_BP_5	binary	0	1	2
EP_EP_5	binary	0	1	2
EP_VCM_5	ordinal	0	2	3
EP_BP_6	binary	0	1	2
EP_EP_6	binary	0	1	2
EP_VCM_6	ordinal	0	2	3
BP_dot_UP_1	binary	0	1	2
BP_dot_DOWN_1	binary	0	1	2
BP_dot_UP_2	binary	0	1	2
BP_dot_DOWN_2	binary	0	1	2
BP_dot_UP_3	binary	0	1	2
BP_dot_DOWN_3	binary	0	1	2
BP_dot_UP_4	binary	0	1	2
BP_dot_DOWN_4	binary	0	1	2
BP_dot_UP_5	binary	0	1	2
BP_dot_DOWN_5	binary	0	1	2
BP_dot_UP_6	binary	0	1	2
BP_dot_DOWN_6	binary	0	1	2
EP_dot_1	binary	0	1	2
EP_dot_2	binary	0	1	2
EP_dot_3	binary	0	1	2
EP_dot_4	binary	0	1	2
EP_dot_5	binary	0	1	2
EP_dot_6	binary	0	1	2
Dot_dot_1	binary	0	1	2
Dot_dot_2	binary	0	1	2
Dot_dot_3	binary	0	1	2
Dot_dot_4	binary	0	1	2
Dot_dot_5	binary	0	1	2
Dot_dot_6	binary	0	1	2
EP_S_Shape_1	ordinal	0	2	3
EP_clock_1	ordinal	0	3	4
EP_UP_BP_1	binary	0	1	2
EP_DOWN_BP_1	binary	0	1	2

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Name	Type	Min	Max	Num val
EP_S_Shape_2	ordinal	0	2	3
EP_clock_2	ordinal	0	3	4
EP_UP_BP_2	binary	0	1	2
EP_DOWN_BP_2	binary	0	1	2
EP_S_Shape_3	ordinal	0	2	3
EP_clock_3	ordinal	0	3	4
EP_UP_BP_3	binary	0	1	2
EP_DOWN_BP_3	binary	0	1	2
EP_S_Shape_4	ordinal	0	2	3
EP_clock_4	ordinal	0	3	4
EP_UP_BP_4	binary	0	1	2
EP_DOWN_BP_4	binary	0	1	2
EP_S_Shape_5	ordinal	0	2	3
EP_clock_5	ordinal	0	3	4
EP_UP_BP_5	binary	0	1	2
EP_DOWN_BP_5	binary	0	1	2
EP_S_Shape_6	ordinal	0	2	3
EP_clock_6	ordinal	0	3	4
EP_UP_BP_6	binary	0	1	2
EP_DOWN_BP_6	binary	0	1	2

There are no missing values. The data were split as follows:

Validation set: `X[4096, 120] Y[4096, 5]`

```
EU:  1113
HU:  875
bL:  1105
jL:  837
tL:  1110
```

Final set: `X[4096, 120] Y[4096, 5]`

```
dL:  966
hL:  1188
kL:  896
qL:  982
sL:  863
```

Development set: `X[150205, 120] Y[150205, 52]`

```
AU:   7
BU:   2
CU:   1
DU:   773
EU:   4712
FU:   2
HU:   506
IU:   67
JU:   2
KU:   552
LU:   8
NU:   7
QU:   182
RU:   4
SU:   777
TU:   372
VU:   3
WU:   2
XU:   161
YU:   6
aL:   27219
bL:   3462
cL:   567
dL:   2204
eL:   7
fL:   4225
hL:   6969
iL:   35
jL:   483
kL:   2722
lL:   16345
mL:   9475
nL:   8276
qL:   2270
rL:   4582
```

```
sL:   360
tL:   3217
uL:   14
vL:   9750
wL:   468
xL:   557
yL:   9201
zL:   416
```

Transfer labels (50000 labels):

```
aL:   25610
lL:   15407
rL:   4301
vL:   9152
yL:   8687
```

4.6. Baseline results

We show first the ridge regression performances obtained by separating one class vs. the rest, training and testing on a balanced subset of examples.

```
Class 50 -- xL = 619 patterns -- AUC=0.9411
Class 36 -- jL = 1350 patterns -- AUC=0.9168
Class 19 -- SU = 958 patterns -- AUC=0.9135
Class 49 -- wL = 534 patterns -- AUC=0.9134
Class 30 -- dL = 3477 patterns -- AUC=0.9080
Class 20 -- TU = 470 patterns -- AUC=0.9078
Class 4 -- DU = 849 patterns -- AUC=0.9045
Class 45 -- sL = 1274 patterns -- AUC=0.8987
Class 52 -- zL = 537 patterns -- AUC=0.8961
Class 37 -- kL = 3734 patterns -- AUC=0.8861
Class 48 -- vL = 10828 patterns -- AUC=0.8766
Class 34 -- hL = 8677 patterns -- AUC=0.8709
Class 17 -- QU = 194 patterns -- AUC=0.8668
Class 11 -- KU = 597 patterns -- AUC=0.8584
Class 8 -- HU = 1450 patterns -- AUC=0.8555
Class 28 -- bL = 4858 patterns -- AUC=0.8543
Class 5 -- EU = 6103 patterns -- AUC=0.8491
Class 29 -- cL = 677 patterns -- AUC=0.8472
Class 46 -- tL = 4672 patterns -- AUC=0.8434
Class 27 -- aL = 29217 patterns -- AUC=0.8399
Class 43 -- qL = 3437 patterns -- AUC=0.8384
```

```
Class 51 -- yL = 10939 patterns -- AUC=0.8342
Class 24 -- XU = 180 patterns -- AUC=0.8270
Class 44 -- rL = 5080 patterns -- AUC=0.8221
Class 40 -- nL = 9209 patterns -- AUC=0.8172
Class 38 -- lL = 18869 patterns -- AUC=0.8138
Class 39 -- mL = 10833 patterns -- AUC=0.7895
Class 32 -- fL = 4709 patterns -- AUC=0.7771
Class 1 -- AU = 10 patterns -- AUC=0.5000
Class 2 -- BU = 2 patterns -- AUC=0.5000
Class 3 -- CU = 1 patterns -- AUC=0.5000
Class 6 -- FU = 3 patterns -- AUC=0.5000
Class 7 -- GU = 0 patterns -- AUC=0.5000
Class 10 -- JU = 2 patterns -- AUC=0.5000
Class 12 -- LU = 8 patterns -- AUC=0.5000
Class 13 -- MU = 1 patterns -- AUC=0.5000
Class 14 -- NU = 8 patterns -- AUC=0.5000
Class 15 -- OU = 0 patterns -- AUC=0.5000
Class 16 -- PU = 0 patterns -- AUC=0.5000
Class 18 -- RU = 6 patterns -- AUC=0.5000
Class 21 -- UU = 0 patterns -- AUC=0.5000
Class 22 -- VU = 5 patterns -- AUC=0.5000
Class 23 -- WU = 2 patterns -- AUC=0.5000
Class 25 -- YU = 8 patterns -- AUC=0.5000
Class 26 -- ZU = 0 patterns -- AUC=0.5000
Class 31 -- eL = 7 patterns -- AUC=0.5000
Class 33 -- gL = 0 patterns -- AUC=0.5000
Class 35 -- iL = 41 patterns -- AUC=0.5000
Class 41 -- oL = 0 patterns -- AUC=0.5000
Class 42 -- pL = 0 patterns -- AUC=0.5000
Class 47 -- uL = 16 patterns -- AUC=0.5000
Class 9 -- IU = 79 patterns -- AUC=0.0385
```

The performances of ridge regression are rather good on the classes selected for validation and final testing, when training and testing on a balanced subset of examples (half of the examples ending up in the training set and half in the test set):

Validation set:

```
Class 4 -- DU = 837 patterns -- AUC=0.8802
Class 2 -- BU = 875 patterns -- AUC=0.8193
Class 3 -- CU = 1105 patterns -- AUC=0.8172
Class 5 -- EU = 1110 patterns -- AUC=0.7938
Class 1 -- AU = 1113 patterns -- AUC=0.7470
```

Final evaluation set:

```
Class 1 -- AU = 966 patterns -- AUC=0.9348
Class 3 -- CU = 896 patterns -- AUC=0.8910
Class 2 -- BU = 1188 patterns -- AUC=0.8663
Class 5 -- EU = 863 patterns -- AUC=0.8336
Class 4 -- DU = 982 patterns -- AUC=0.7712
```

However, when we make learning curves, the classes are not well balanced and the number of training examples is small, so the performances are not as good. We show results on raw data in Figure 5. The baseline results obtained by preprocessing with K-means clustering are even worse. Note that we verified that rotating the space and quantizing does not harm performance. The baseline results indicate that this dataset is much harder than ULE.

Table 8: Baseline results (normalized ALC for 64 training examples).

AVICENNA	**Valid**	**Final**
Raw	**0.1034**	**0.1501**
Preprocessed	0.0856	0.0973

5. C – HARRY

5.1. Topic

The task of HARRY (Human Action Recognition) is action recognition in movies.

5.2. Sources

5.2.1. Original owners

Ivan Laptev and Barbara Caputo collected and made publicly available the KTH human action recognition datasets. Marcin Marszałek, Ivan Laptev and Cordelia Schmid collected and made publicly available the Hollywood 2 dataset of human actions and scenes.

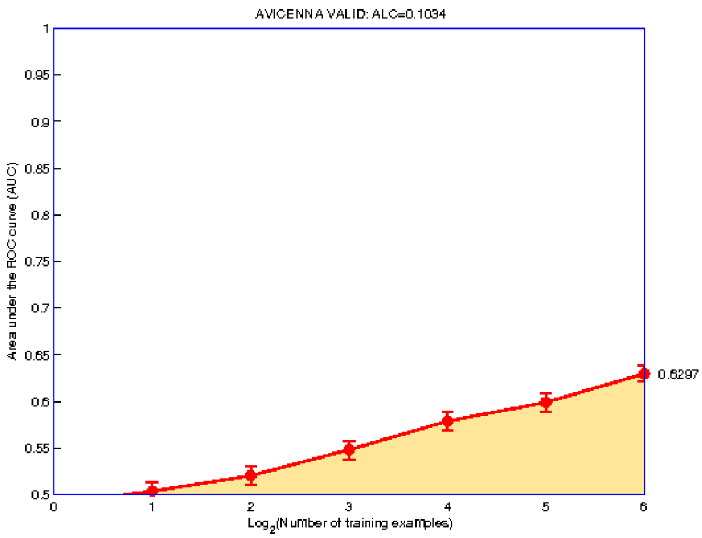
We are grateful to Graham Taylor for providing us with the data in preprocessed STIP feature format and for providing Matlab code to read the format and create a bag-of-STIP-features representation.

5.2.2. Donor of database

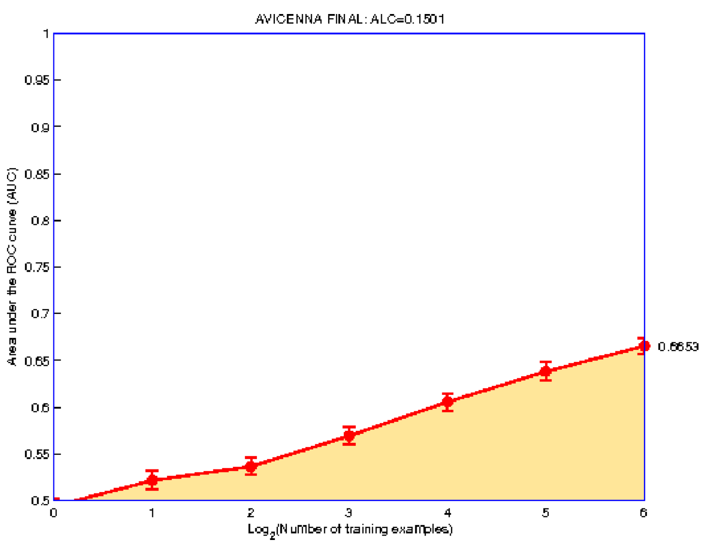
This version of the database was prepared for the "unsupervised and transfer learning challenge" by Isabelle Guyon, 955 Creston Road, Berkeley, CA 94708, USA (`isabelle@clopinet.com`).

5.2.3. Date prepared for the challenge:

November–December 2010.



(*a*)



(*b*)

Figure 5: Baseline results on raw data (top valid, bottom final).

Figure 6: Action Recognition in Movies

5.3. Past Usage

The original Hollywood-2 dataset contains 12 classes of human actions and 10 classes of scenes distributed over 3669 video clips and approximately 20.1 hours of video in total. The dataset intends to provide a comprehensive benchmark for human action recognition in realistic and challenging settings. The dataset is composed of video clips extracted from 69 movies, it contains approximately 150 samples per action class and 130 samples per scene class in training and test subsets. A part of this dataset was originally used in the paper "Actions in Context", Marszałek et al. in Proc. CVPR'09. Hollywood-2 is an extension of the earlier Hollywood dataset.

The feature representation called STIP on which we based the preprocessing have been successfully used for action recognition in the paper "Learning Realistic Human Actions from Movies", Ivan Laptev, Marcin Marszałek, Cordelia Schmid and Benjamin Rozenfeld; in Proc. CVPR'08. See also the on-line paper description `http://www.irisa.fr/vista/actions/`.

The results on classifying KTH actions reported by the authors are listed in Table 9.

Table 9: Results on classifying KTH actions reported by authors

Method	Schuldt et al. [icpr04]	Niebles et al. [bmvc06]	Wong et al. [iccv07]	ours
Accuracy	71.7%	81.5%	86.7%	91.8%

And those from Hollywood movie actions are listed in Table 10.

The Automatic training set was constructed using automatic action annotation based on movie scripts and contains over 60% correct action labels. The Clean training set was obtained by manually correcting the Automatic set.

5.4. Experimental Design

The data were preprocessed into STIP features using the code of Ivan Laptev: `http://www.irisa.fr/vista/Equipe/People/Laptev/download/stip-1.0-winlinux.zip`.

The STIP features are described in:

Table 10: Hollywood movie actions

	Clean	Automatic	Chance
AnswerPhone	32.1%	16.4%	10.6%
GetOutCar	41.5%	16.4%	6.0%
HandShake	32.3%	9.9%	8.8%
HugPerson	40.6%	26.8%	10.1%
Kiss	53.3%	45.1%	23.5%
SitDown	38.6%	24.8%	13.8%
SitUp	18.2%	10.4%	4.6%
StandUp	50.5%	33.6%	22.6%

"On Space-Time Interest Points" (2005), I. Laptev; in *International Journal of Computer Vision*, vol 64, number 2/3, pp.107–123.

This yielded both HOG and HOF features for every video frame (in the original format, there are 6 ints followed by 1 float confidence value followed by 162 float HOG/HOF features). The code does not implement scale selection, Instead interest points are detected at multiple spatial and temporal scales. The implemented descriptors HOG (Histograms of Oriented Gradients) and HOF (Histograms of Optical Flow) are computed for 3D video patches in the neighborhood of detected STIPs.

The final representation is a "bag of STIP features". The vectors of HOG/HOF features were clustered into 5000 clusters (we used the KTH data for clustering), using on on-line version of the kmeans algorithm. Each video frame was then assigned to its closest cluster center. We obtained a sparse representation of 5000 features, each feature representing the frequency of presence of a given STIP feature cluster center in a video clip.

To create a large dataset of video examples, the original videos were cut in smaller clips:

Each Hollywood2 movie clip was further split into 40 subsequences and each KTH movie clip was further split into 4 subsequences. Not normalization for sequence length was performed.

5.5. Data statistics

Table 11: Data statistics for HARRY

Dataset	Domain	Feat. num.	Sparsity (%)	Development num.	Transfer num.	Validation num	Final eval. num.
HARRY	Human Action Recognition	5000	98.12	69652	20000	4096	4096

All variables are numeric (no categorical variable). There are no missing values. The target variables are categorical. The patterns and categories selected for the validation and final evaluation sets are all from the KTH dataset. Here is class label composition of the data subsets:

Validation set: `X[4096, 5000] Y[4096, 3]`

```
boxing:         1370
handclapping:   1377
jogging:        1349
```

Final set: `X[4096, 5000] Y[4096, 3]`

```
handwaving:   1360
running:      1369
walking:      1367
```

Development set: `X[69652, 5000] Y[69652, 18]`

```
boxing:         218
handclapping:   207
handwaving:     232
jogging:        251
running:        231
walking:        233
AnswerPhone:    5200
DriveCar:       7480
Eat:            2920
FightPerson:    4960
GetOutCar:      4320
HandShake:      3080
HugPerson:      5200
Kiss:           8680
Run:            11040
SitDown:        8480
SitUp:          2440
StandUp:        11120
```

Transfer labels (20000 labels):

```
DriveCar:      5831
Eat:           2213
FightPerson:   3847
Run:           8547
```

5.6. Baseline results

The data were preprocessed with kmeans clustering as described in Section 3.

Table 12: Baseline results (normalized ALC for 64 training examples).

HARRY	Valid	Final
Raw	**0.6264**	**0.6017**
Preprocessed	0.2230	0.2292

6. D – RITA

6.1. Topic

The task of RITA (Recognition of Images of Tiny Area) is object recognition.

6.2. Sources

6.2.1. Original owners

Antonio Torralba, Rob Fergus, and William T. Freeman, collected and made available publicly the 80 million tiny image dataset. Vinod Nair and Geoffrey Hinton collected and made available publicly the CIFAR datasets.

6.2.2. Donor of database

This version of the database was prepared for the "unsupervised and transfer learning challenge" by Isabelle Guyon, 955 Creston Road, Berkeley, CA 94708, USA (`isabelle@clopinet.com`).

6.2.3. Date prepared for the challenge:

December 2010.

6.3. Past usage

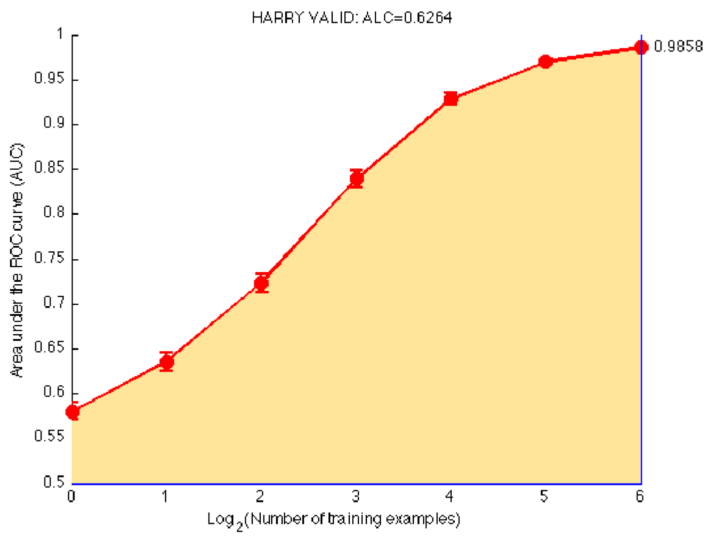
Learning Multiple Layers of Features from Tiny Images, by Alex Krizhevsky, Master thesis, Univ. Toronto, 2009.

Semi-Supervised Learning in Gigantic Image Collections, Rob Fergus, Yair Weiss and Antonio Torralba, *Advances in Neural Information Processing Systems (NIPS).*

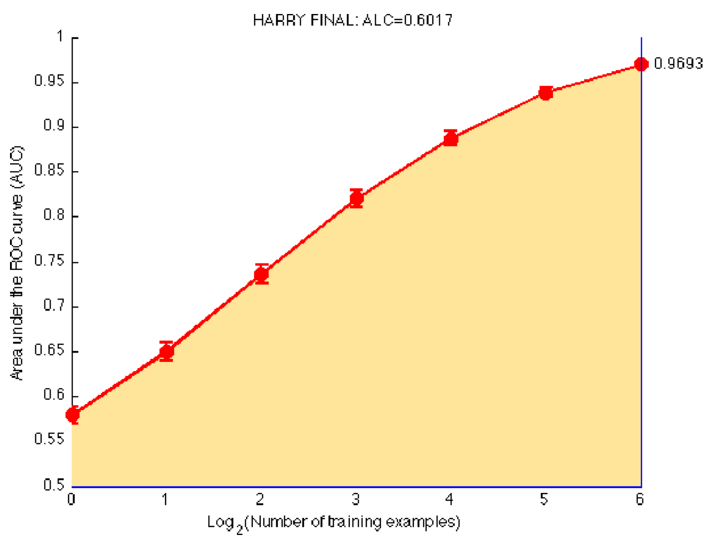
See also many other citations of CIFAR-10 and CIFAR-100 on Google.

6.4. Experimental design

We merged the CIFAR-10 and the CIFAR-100 datasets. The CIFAR-10 dataset consists of 60000 32×32 colour images in 10 classes, with 6000 images per class. The original categories are:



(a)



(b)

Figure 7: Baseline results on raw data (top valid, bottom final).

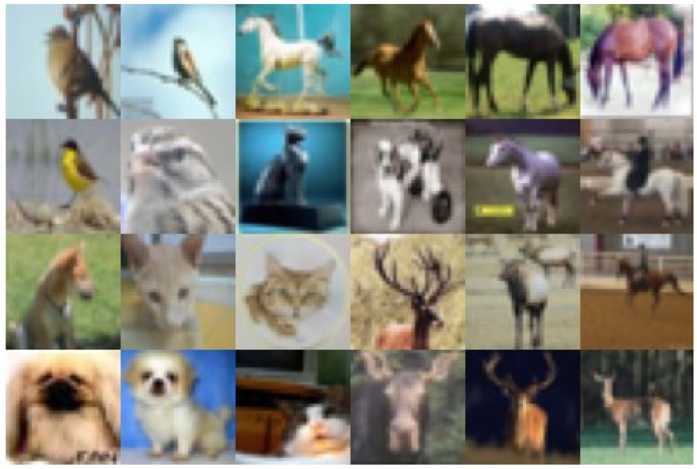


Figure 8: Recognition of Images of Tiny Area

airplane

automobile

bird

cat

deer

dog

frog

horse

ship

truck

The CIFAR-100 dataset is similar to the CIFAR-10, except that it has 100 classes containing 600 images each. The 100 classes in the CIFAR-100 are grouped into 20 superclasses. Each image comes with a "fine" label (the class to which it belongs) and a "coarse" label (the superclass to which it belongs).

Table 13 lists the classes in the CIFAR-100.

The raw data came as 32×32 tiny images coded with 8-bit RGB colors (i.e. 3×32 features with 256 possible values). We converted RGB to HSV and quantized the results as 8-bit integers. This yielded $30 \times 30 \times 3 = 900 \times 3$ features. We then preprocessed the gray level image to extract edges. This yielded 30×30 features (1 border pixel was removed). We then cut the images into patches of 10×10 pixels and ran kmeans clustering (an on-line version) to create 144 cluster centers. We used these cluster centers as a dictionary to create features corresponding to the presence of one the 144 shapes at one of 25 positions on a grid. This created another $144 \times 25 = 3600$ features.

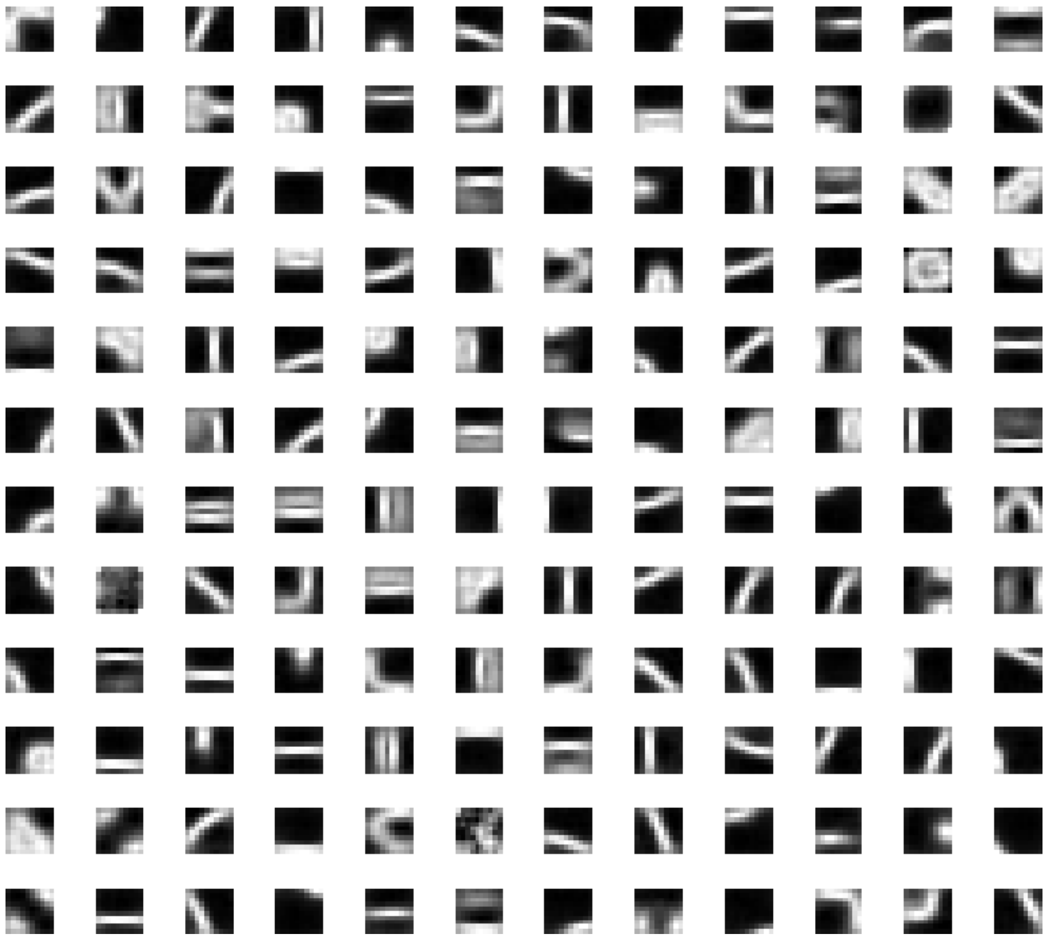


Figure 9: 144 cluster centers computed from patches of line images.

Figure 10: Example of tiny image.

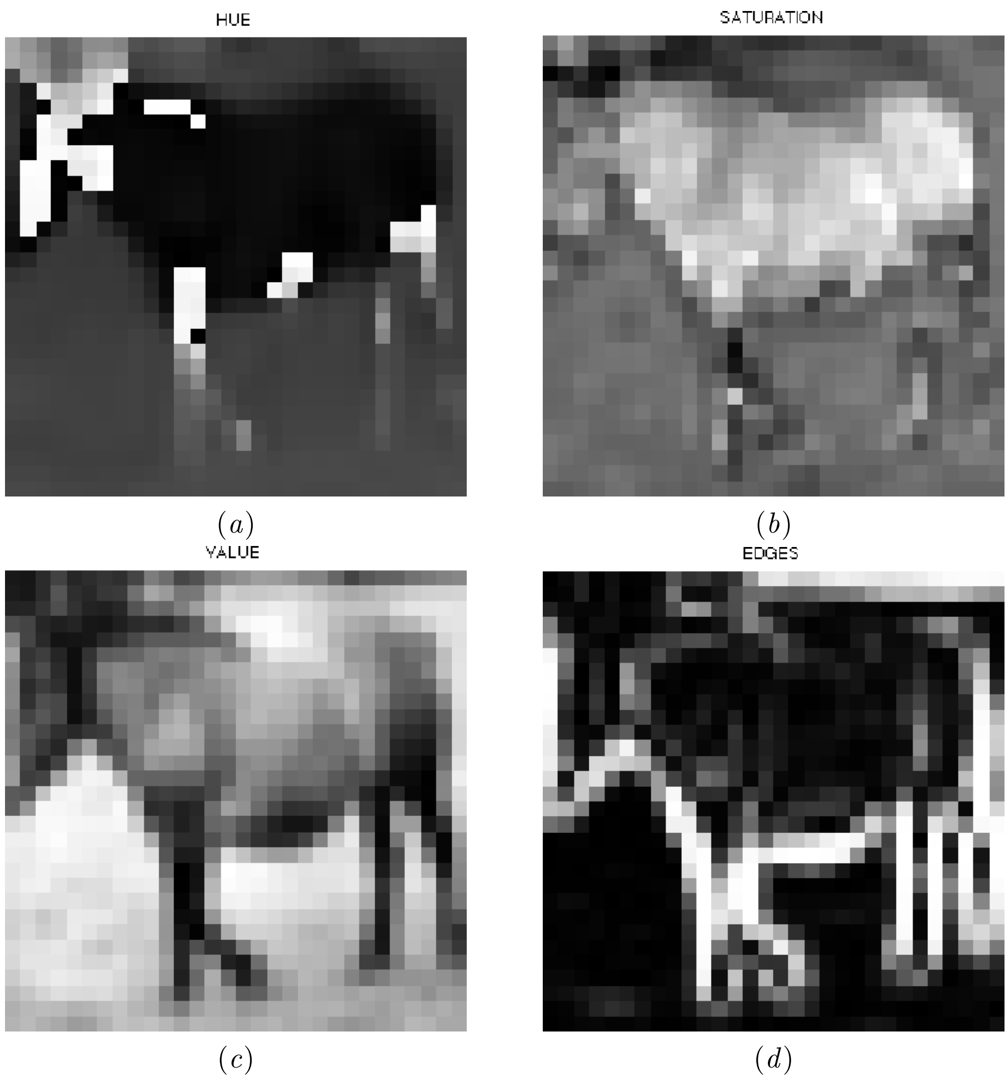


Figure 11: Image represented by Hue, Saturation, Value, and Edges (3600 features). We computed another 3600 features from the edge image using the matched filters computed by clustering.

Table 13: Classes in the CIFAR-100

Superclass	**Classes**
fish	aquarium fish, flatfish, ray, shark, trout
flowers	orchids, poppies, roses, sunflowers, tulips
food containers	bottles, bowls, cans, cups, plates
fruit and vegetables	apples, mushrooms, oranges, pears, sweet peppers
household electrical devices	clock, computer keyboard, lamp, telephone, television
household furniture	bed, chair, couch, table, wardrobe
insects	bee, beetle, butterfly, caterpillar, cockroach
large carnivores	bear, leopard, lion, tiger, wolf
large man-made outdoor things	bridge, castle, house, road, skyscraper
large natural outdoor scenes	cloud, forest, mountain, plain, sea
large omnivores and herbivores	camel, cattle, chimpanzee, elephant, kangaroo
medium-sized mammals	fox, porcupine, possum, raccoon, skunk
non-insect invertebrates	crab, lobster, snail, spider, worm
people	baby, boy, girl, man, woman
reptiles	crocodile, dinosaur, lizard, snake, turtle
small mammals	hamster, mouse, rabbit, shrew, squirrel
trees	maple, oak, palm, pine, willow
vehicles 1	bicycle, bus, motorcycle, pickup truck, train
vehicles 2	lawn-mower, rocket, streetcar, tank, tractor

6.5. Data statistics

Table 14: Data statistics for RITA

Dataset	Domain	Feat. num.	Sparsity (%)	Development num.	Transfer num.	Validation num	Final eval. num.
RITA	Object recognition	7200	1.19	111808	24000	4096	4096

All variables are numeric (no categorical variable). There are no missing values. The target variables are categorical. All the categories of the validation and final evaluation sets are from the CIFAR-10 dataset. Here is class label composition of the data subsets:

Validation set: `X[4096, 7200] Y[4096, 3]`

```
automobile:  1330
horse:       1377
truck:       1389
```

Final set: `X[4096, 7200] Y[4096, 3]`

```
airplane:  1384
```

frog:	1370
ship:	1342

Development set: `X[111808, 7200] Y[111808, 110]`

airplane:	4616
automobile:	4670
bird:	6000
cat:	6000
deer:	6000
dog:	6000
frog:	4630
horse:	4623
ship:	4658
truck:	4611
fruit_and_vegetables.apple:	600
fish.aquarium_fish:	600
people.baby:	600
large_carnivores.bear:	600
aquatic_mammals.beaver:	600
household_furniture.bed:	600
insects.bee:	600
insects.beetle:	600
vehicles_1.bicycle:	600
food_containers.bottle:	600
food_containers.bowl:	600
people.boy:	600
large_man-made_outdoor_things.bridge:	600
vehicles_1.bus:	600
insects.butterfly:	600
large_omnivores_and_herbivores.camel:	600
food_containers.can:	600
large_man-made_outdoor_things.castle:	600
insects.caterpillar:	600
large_omnivores_and_herbivores.cattle:	600
household_furniture.chair:	600
large_omnivores_and_herbivores.chimpanzee:	600

household_electrical_devices.clock:	600
large_natural_outdoor_scenes.cloud:	600
insects.cockroach:	600
household_furniture.couch:	600
non-insect_invertebrates.crab:	600
reptiles.crocodile:	600
food_containers.cup:	600
reptiles.dinosaur:	600
aquatic_mammals.dolphin:	600
large_omnivores_and_herbivores.elephant:	600
fish.flatfish:	600
large_natural_outdoor_scenes.forest:	600
medium_mammals.fox:	600
people.girl:	600
small_mammals.hamster:	600
large_man-made_outdoor_things.house:	600
large_omnivores_and_herbivores.kangaroo:	600
household_electrical_devices.keyboard:	600
household_electrical_devices.lamp:	600
vehicles_2.lawn_mower:	600
large_carnivores.leopard:	600
large_carnivores.lion:	600
reptiles.lizard:	600
non-insect_invertebrates.lobster:	600
people.man:	600
trees.maple_tree:	600
vehicles_1.motorcycle:	600
large_natural_outdoor_scenes.mountain:	600
small_mammals.mouse:	600
fruit_and_vegetables.mushroom:	600
trees.oak_tree:	600
fruit_and_vegetables.orange:	600
flowers.orchid:	600
aquatic_mammals.otter:	600
trees.palm_tree:	600

`fruit_and_vegetables.pear:`	600
`vehicles_1.pickup_truck:`	600
`trees.pine_tree:`	600
`large_natural_outdoor_scenes.plain:`	600
`food_containers.plate:`	600
`flowers.poppy:`	600
`medium_mammals.porcupine:`	600
`medium_mammals.possum:`	600
`small_mammals.rabbit:`	600
`medium_mammals.raccoon:`	600
`fish.ray:`	600
`large_man-made_outdoor_things.road:`	600
`vehicles_2.rocket:`	600
`flowers.rose:`	600
`large_natural_outdoor_scenes.sea:`	600
`aquatic_mammals.seal:`	600
`fish.shark:`	600
`small_mammals.shrew:`	600
`medium_mammals.skunk:`	600
`large_man-made_outdoor_things.skyscraper:`	600
`non-insect_invertebrates.snail:`	600
`reptiles.snake:`	600
`non-insect_invertebrates.spider:`	600
`small_mammals.squirrel:`	600
`vehicles_2.streetcar:`	600
`flowers.sunflower:`	600
`fruit_and_vegetables.sweet_pepper:`	600
`household_furniture.table:`	600
`vehicles_2.tank:`	600
`household_electrical_devices.telephone:`	600
`household_electrical_devices.television:`	600
`large_carnivores.tiger:`	600
`vehicles_2.tractor:`	600
`vehicles_1.train:`	600
`fish.trout:`	600

`flowers.tulip:`	600
`reptiles.turtle:`	600
`household_furniture.wardrobe:`	600
`aquatic_mammals.whale:`	600
`trees.willow_tree:`	600
`large_carnivores.wolf:`	600
`people.woman:`	600
`non-insect_invertebrates.worm:`	600

Transfer labels (24000 labels):

`bird:`	6000
`cat:`	6000
`deer:`	6000
`dog:`	6000

6.6. Baseline results

The data were preprocessed with kmeans clustering as described in Section 3.

Table 15: Baseline results (normalized ALC for 64 training examples).

RITA	Valid	Final
Raw	**0.2504**	**0.4133**
Preprocessed	0.2417	0.3413

7. E – SYLVESTER

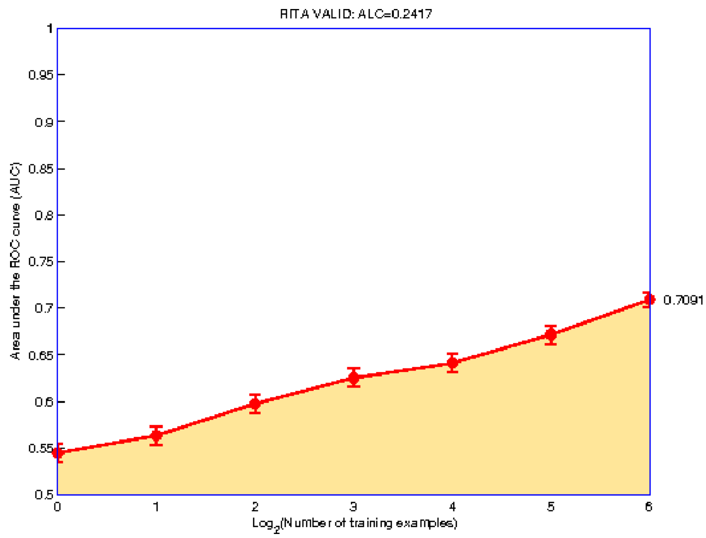
7.1. Topic

The task of SYLVESTER is to classify forest cover types. The task was carved out of data from the US Forest Service (USFS). The data include 7 labels corresponding to forest cover types. We used 2 for transfer learning (training), 2 for validation and 3 for testing.

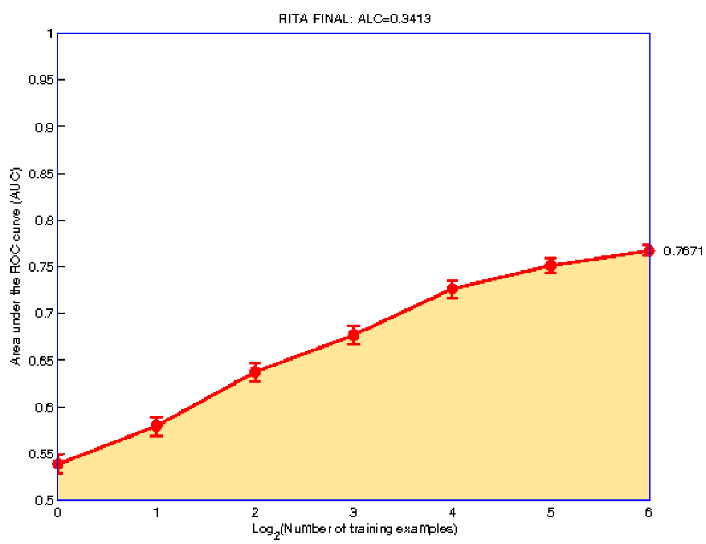
7.2. Sources

7.2.1. Original owners

Remote Sensing and GIS Program
Department of Forest Sciences
College of Natural Resources
Colorado State University
Fort Collins, CO 80523



(a)



(b)

Figure 12: Baseline results on preprocessed data (top valid, bottom final).

(contact Jock A. Blackard, jblackard/wo_ftcol@fs.fed.us
or Dr. Denis J. Dean, denis@cnr.colostate.edu)
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7.2.2. Donor of database

This version of the database was prepared for the "unsupervised and transfer learning challenge" by Isabelle Guyon, 955 Creston Road, Berkeley, CA 94708, USA (isabelle@clopinet.com).

7.2.3. Date received (original data):

August 28, 1998, UCI Machine Learning Repository, under the name Forest Cover Type.

7.2.4. Date prepared for the challenge:

September–November 2010.

7.3. Past usage

Blackard, Jock A. 1998. "Comparison of Neural Networks and Discriminant Analysis in Predicting Forest Cover Types." Ph.D. dissertation. Department of Forest Sciences. Colorado State University. Fort Collins, Colorado.

Classification performance with first 11,340 records used for training data, next 3,780 records used for validation data, and last 565,892 records used for testing data subset: – 70% backpropagation – 58% Linear Discriminant Analysis.

The subtask SYLVA prepared for the "performance prediction challenge" and the "agnostic learning vs. prior knowledge" (ALvsPK) challenge is a 2-class classification problem (Ponderosa pine vs. others). The best results were obtained with Logitboost by Roman Lutz who obtained 0.4% error in the PK track and 0.6% error in the AL track. See http://clopinet.com/isabelle/Projects/agnostic/Results.html. The data were also used in the "active learning challenge" under the name "SYLVA" during the development phase and "F" (for FOREST) during the final test phase. The best entrants (Intel team) obtained a 0.8 area under the learning curve, see http://www.causality.inf.ethz.ch/activelearning.php?page=results.

7.4. Experimental design

The original data comprises a total of 581012 instances (observations) grouped in 7 classes (forest cover types) and having 54 attributes (features) corresponding to 12 measures (10 quantitative variables, 4 binary wilderness areas and 40 binary soil type variables). The actual forest cover type for a given observation (30×30 meter cell) was determined from US Forest Service (USFS) Region 2 Resource Information System (RIS) data. Independent variables were derived from data originally obtained from US Geological Survey (USGS) and USFS data. Data is in raw form (not scaled) and contains binary (0 or 1) columns of data for qualitative independent variables (wilderness areas and soil types).

7.4.1. Variable Information

Given in Table 16 are the variable name, variable type, the measurement unit and a brief description. The forest cover type is the classification problem. The order of this listing corresponds to the order of numerals along the rows of the database.

7.4.2. Code Designations

Wilderness Areas:

- **1** – Rawah Wilderness Area
- **2** – Neota Wilderness Area
- **3** – Comanche Peak Wilderness Area
- **4** – Cache la Poudre Wilderness Area

Soil Types:

- **1 to 40** : based on the USFS Ecological Landtype Units for this study area.

Forest Cover Types:

- **1** – Spruce/Fir
- **2** – Lodgepole Pine
- **3** – Ponderosa Pine
- **4** – Cottonwood/Willow

Table 16: Variable Information for SYLVESTER

Name	**Data Type**	**Measurement**	**Description**
Elevation	quantitative	meters	Elevation in meters
Aspect	quantitative	azimuth	Aspect in degrees azimuth
Slope	quantitative	degrees	Slope in degrees
Horizontal_Distance_To_Hydrology	quantitative	meters	Horz Dist to nearest surface water features
Vertical_Distance_To_Hydrology	quantitative	meters	Vert Dist to nearest surface water features
Horizontal_Distance_To_Roadways	quantitative	meters	Horz Dist to nearest roadway
Hillshade_9am	quantitative	0 to 255 index	Hillshade index at 9am, summer solstice
Hillshade_Noon	quantitative	0 to 255 index	Hillshade index at noon, summer soltice
Hillshade_3pm	quantitative	0 to 255 index	Hillshade index at 3pm, summer solstice
Horizontal_Distance_To_Fire_Points	quantitative	meters	Horz Dist to nearest wildfire ignition points
Wilderness_Area	(4 binary columns) qualitative	0 (absence) or 1 (presence)	Wilderness area designation
Soil_Type	(40 binary columns) qualitative	0 (absence) or 1 (presence)	Soil Type designation
Cover_Type	(7 types) integer	1 to 7	Forest Cover Type designation

5 – Aspen

6 – Douglas-fir

7 – Krummholz

7.4.3. Class Distribution

Number of records of Spruce-Fir:	211840
Number of records of Lodgepole Pine:	283301
Number of records of Ponderosa Pine:	35754
Number of records of Cottonwood/Willow:	2747
Number of records of Aspen:	9493
Number of records of Douglas-fir:	17367
Number of records of Krummholz:	20510
Total records:	581012

7.4.4. Data preprocessing and data split

We mixed mixed the classes to get approximately the same error rate in baseline results on the validation set and the final evaluation set.

We used the original data encoding from the data donors, transformed by an invertible linear transform (an isometry). To make it even harder to go back to the original data, non-informative features (distractors) were added, corresponding to randomly permuted column values of the original features, before applying the isometry. We then randomized the order of the features and patterns. We quantized the values between 0 and 999.

7.5. Number of examples and class distribution

Table 17: Statistics on the SYLVESTER data

Dataset	Domain	Feat. type	Feat. num.	Sparsity (%)	Label	Development num.	Transfer num.	Validation num	Final eval. num.
SYLVESTER	Ecology	Numeric	100	0	Binary	572820	10000	4096	4096

There are no missing values. Here is class label composition of the data subsets:

Validation set: `X[4096, 100] Y[4096, 1]`

```
Ponderosa Pine:   2044
Aspen:            2052
```

Final set: `X[4096, 100] Y[4096, 1]`

```
Spruce/Fir:    1319
Douglas-fir:   1404
```

```
Krummholz:    1373
```

Development set: `X[572820, 100] Y[572820, 1]`

```
Spruce/Fir:          210521
Lodgepole Pine:      283301
Ponderosa Pine:      33710
Cottonwood/Willow:   2747
Aspen:               7441
Douglas-fir:         15963
Krummholz:           19137
```

Transfer labels (10000 labels):

```
Lodgepole Pine:      9891
Cottonwood/Willow:   109
```

7.6. Type of input variables and variable statistics

100 numeric variables transformed via a random isometry from the raw input variables to which 46 distractors were added. The distractors were obtained by picking real variables and randomizing the order of the values. The final variables were quantized between 0 and 999.

7.7. Baseline results

We show results using our baseline classifier shown in appendix. The prepreprocessing in kmeans clustering (20 clusters).

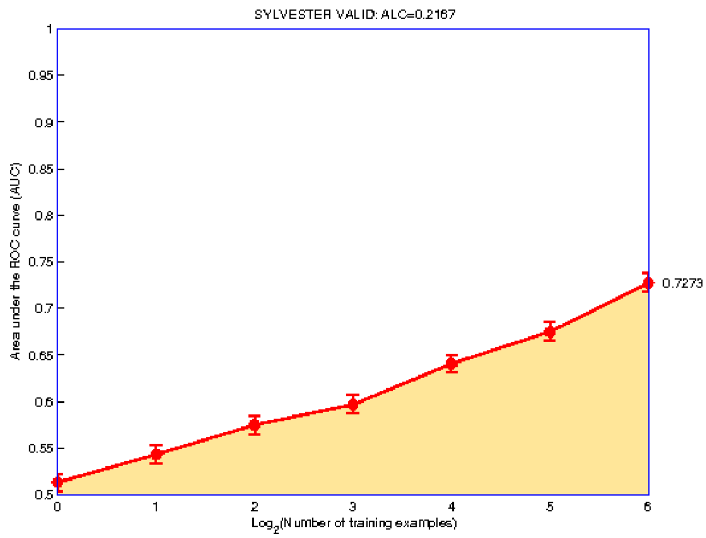
Table 18: Baseline results (normalized ALC for 64 training examples).

SYLVESTER	Valid	Final
Raw	**0.2167**	**0.3095**
Preprocessed	0.1670	0.2362

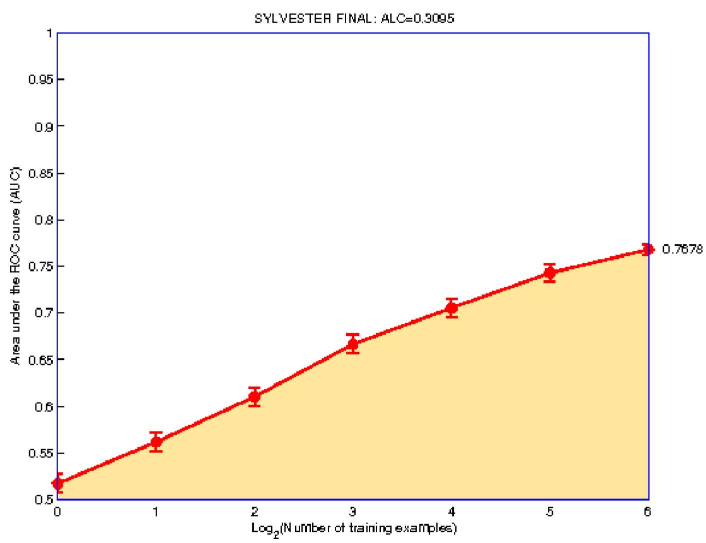
8. F – Terry

8.1. Topic

The task of TERRY is the Text Recognition dataset.



(a)



(b)

Figure 13: Baseline results on raw data (top valid, bottom final).

8.2. Sources

8.2.1. Original owners

The data were donated by Reuters and downloaded from: Lewis, D. D. RCV1-v2/LYRL2004: The LYRL2004 Distribution of the RCV1-v2 Text Categorization Test Collection (12-Apr-2004 Version). http://www.jmlr.org/papers/volume5/lewis04a/lyrl2004_rcv1v2_README.htm.

8.2.2. Donor of database

This version of the database was prepared for the "unsupervised and transfer learning challenge" by Isabelle Guyon, 955 Creston Road, Berkeley, CA 94708, USA (isabelle@clopinet.com).

8.2.3. Date prepared for the challenge:

November–December 2010.

8.3. Past usage

Lewis, D. D.; Yang, Y.; Rose, T.; and Li, F. RCV1: A New Benchmark Collection for Text Categorization Research. Journal of Machine Learning Research, 5:361-397, 2004. http://www.jmlr.org/papers/volume5/lewis04a/lewis04a.pdf.

8.4. Experimental design

We used a subset of the 800,000 documents of the RCV1-v2 data collection, formatted in a bag-of-words representation. The representation uses 47,236 unique stemmed tokens. The representation was obtained from on-line appendix B.13. The list of stems was found in on-line appendix B14. We used as target values the topic categories (on-line appendices 3 and 8). We considered all levels of the hierarchy to select the most promising categories.

The features were obfuscated by making a non-linear transformation of the values then quantizing them between 0 and 999. Further, the raws and lines of the data matrix were permuted.

8.5. Data statistics

Table 19: Data statistics for TERRY

Dataset	Domain	Feat. num.	Sparsity (%)	Development num.	Transfer num.	Validation num	Final eval. num.
TERRY	Text recognition	47236	99.84	217034	40000	4096	4096

All variables are numeric (no categorical variable). There are no missing values. The target variables are categorical. The data are very sparse, so they were stored in a sparse matrix. Here is class label composition of the data subsets:

Validation set: `X[4096, 47236] Y[4096, 5]`

ENERGY MARKETS:	808
EUROPEAN COMMUNITY:	886
PRIVATISATIONS:	817
MANAGEMENT:	863
ENVIRONMENT AND NATURAL WORLD:	826

Final set: `X[4096, 47236] Y[4096, 5]`

SPORTS:	797
CREDIT RATINGS:	804
DISASTERS AND ACCIDENTS:	829
ELECTIONS:	856
LABOUR ISSUES:	829

Development set: `X[217034, 47236] Y[217034, 103]`

STRATEGY/PLANS:	6944
LEGAL/JUDICIAL:	2898
REGULATION/POLICY:	10279
SHARE LISTINGS:	2166
PERFORMANCE:	42290
ACCOUNTS/EARNINGS:	21832
ANNUAL RESULTS:	2243
COMMENT/FORECASTS:	21315
INSOLVENCY/LIQUIDITY:	494
FUNDING/CAPITAL:	11885
SHARE CAPITAL:	5378
BONDS/DEBT ISSUES:	3147
LOANS/CREDITS:	705
CREDIT RATINGS:	1453
OWNERSHIP CHANGES:	13853
MERGERS/ACQUISITIONS:	11739
ASSET TRANSFERS:	1312
PRIVATISATIONS:	1370
PRODUCTION/SERVICES:	7749
NEW PRODUCTS/SERVICES:	1967

RESEARCH/DEVELOPMENT:	751
CAPACITY/FACILITIES:	8895
MARKETS/MARKETING:	11832
DOMESTIC MARKETS:	1199
EXTERNAL MARKETS:	1999
MARKET SHARE:	282
ADVERTISING/PROMOTION:	513
CONTRACTS/ORDERS:	4360
DEFENCE CONTRACTS:	339
MONOPOLIES/COMPETITION:	1264
MANAGEMENT:	2245
MANAGEMENT MOVES:	2044
LABOUR:	2971
CORPORATE/INDUSTRIAL:	105241
ECONOMIC PERFORMANCE:	2462
MONETARY/ECONOMIC:	7044
MONEY SUPPLY:	632
INFLATION/PRICES:	1924
CONSUMER PRICES:	1642
WHOLESALE PRICES:	288
CONSUMER FINANCE:	615
PERSONAL INCOME:	84
CONSUMER CREDIT:	63
RETAIL SALES:	365
GOVERNMENT FINANCE:	12008
EXPENDITURE/REVENUE:	4066
GOVERNMENT BORROWING:	8052
OUTPUT/CAPACITY:	679
INDUSTRIAL PRODUCTION:	482
CAPACITY UTILIZATION:	13
INVENTORIES:	30
EMPLOYMENT/LABOUR:	4087
UNEMPLOYMENT:	484
TRADE/RESERVES:	6412
BALANCE OF PAYMENTS:	933

MERCHANDISE TRADE:	3994
RESERVES:	546
HOUSING STARTS:	104
LEADING INDICATORS:	1556
ECONOMICS:	33239
EUROPEAN COMMUNITY:	5554
EC INTERNAL MARKET:	945
EC CORPORATE POLICY:	559
EC AGRICULTURE POLICY:	620
EC MONETARY/ECONOMIC:	2219
EC INSTITUTIONS:	561
EC ENVIRONMENT ISSUES:	50
EC COMPETITION/SUBSIDY:	524
EC EXTERNAL RELATIONS:	1142
EC GENERAL:	18
GOVERNMENT/SOCIAL:	63881
CRIME, LAW ENFORCEMENT:	8380
DEFENCE:	2506
INTERNATIONAL RELATIONS:	11105
DISASTERS AND ACCIDENTS:	1488
ARTS, CULTURE, ENTERTAINMENT:	1078
ENVIRONMENT AND NATURAL WORLD:	790
FASHION:	76
HEALTH:	1744
LABOUR ISSUES:	4161
OBITUARIES:	184
HUMAN INTEREST:	667
DOMESTIC POLITICS:	15654
BIOGRAPHIES, PERSONALITIES, PEOPLE:	1668
RELIGION:	804
SCIENCE AND TECHNOLOGY:	638
SPORTS:	8671
TRAVEL AND TOURISM:	223
WAR, CIVIL WAR:	9323
ELECTIONS:	3539

WEATHER:	821
WELFARE, SOCIAL SERVICES:	484
EQUITY MARKETS:	12424
BOND MARKETS:	6179
MONEY MARKETS:	13574
INTERBANK MARKETS:	7279
FOREX MARKETS:	6599
COMMODITY MARKETS:	21557
SOFT COMMODITIES:	12155
METALS TRADING:	3092
ENERGY MARKETS:	5162
MARKETS:	51279

Transfer labels (40000 labels):

DOMESTIC POLITICS:	12865
MONEY MARKETS:	11322
REGULATION/POLICY:	8508
GOVERNMENT FINANCE:	9900

8.6. Baseline results

The data were preprocessed with kmeans clustering as described in Section 3.

Table 20: Baseline results (normalized ALC for 64 training examples).

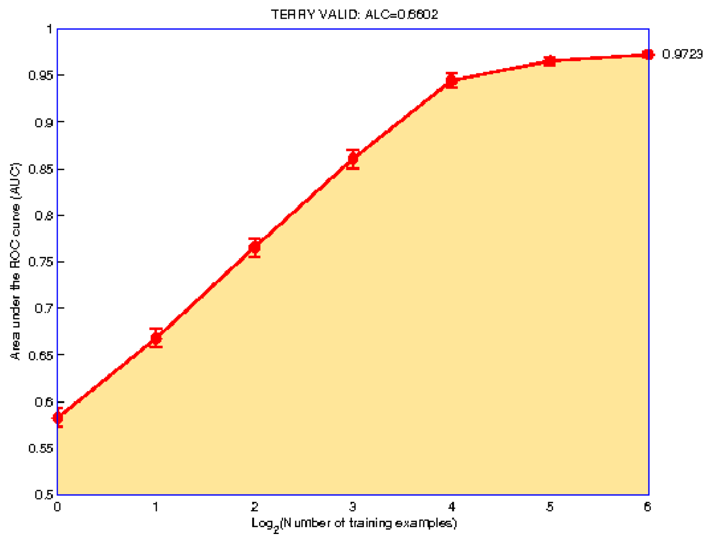
TERRY	Valid	Final
Raw	**0.6969**	**0.7550**
Preprocessed	0.6602	0.3440

We see in Table 20 and Figure 14 that the performances in preprocessed data in the final evaluation set are not good. This is another example of preprocessing overfiting: we used the clusters found with the validation set to preprocess the test set.

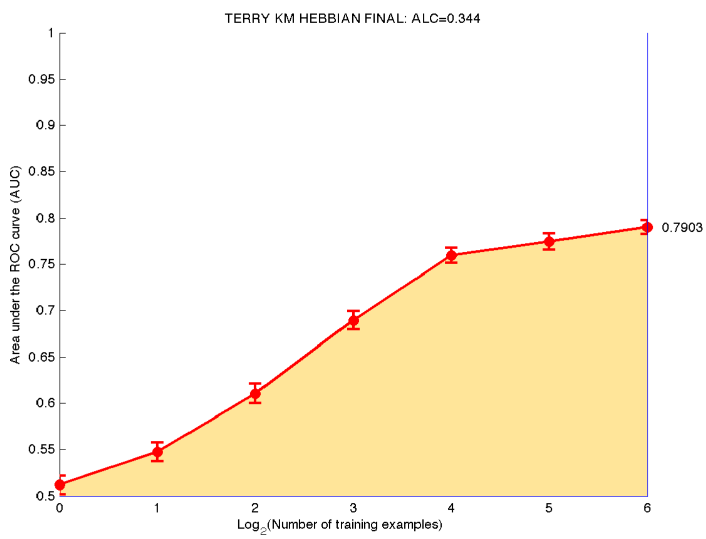
Appendix

Code for the linear classifier

```
function [data, model]=train(model, data)
%[data, model]=train(model, data)
% Simple linear classifier with Hebbian-style learning.
% Inputs:
```



(a)



(b)

Figure 14: Baseline results on preprocessed data (top valid, bottom final).

```
% model      -- A hebbian learning object.
% data       -- A data object.
% Returns:
% model      -- The trained model.
% data       -- A new data structure containing the results.
% Usually works best with standardized data. Standardization is not
% performed here for computational reasons (we put it outside the CV
% loop).


% Isabelle Guyon -- isabelle@clopinet.com -- November 2010


if model.verbosity>0, fprintf('==> Training Hebbian classifier ...
'); end


Posidx=find(data.Y>0);
Negidx=find(data.Y<0);


if pd_check(data)
    % Kernelized version
    model.W=zeros(1, length(data.Y));
    model.W(Posidx)=1/(length(Posidx)+eps);
    model.W(Negidx)=-1/(length(Negidx)+eps);
else
    n=size(data.X, 2);
    Mu1=zeros(1, n); Mu2=zeros(1, n);
    if ~isempty(Posidx)
        Mu1=mean(data.X(Posidx,:), 1);
    end
    if ~isempty(Negidx)
        Mu2=mean(data.X(Negidx,:), 1);
    end
    model.W=Mu1-Mu2;
    B=(Mu1+Mu2)/2;
    model.b0=-model.W*B';
end

% Test the model
if model.test_on_training_data
    data=test(model, data);
end
```

```
if model.verbosity>0, fprintf('done\n'); end
```