Chapter 8. Classification: Ensembles

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Introduction to Data Mining

Turing Award Recipients

…	…	…
1998	Jim Gray	For seminal contributions to **database and transaction processing research**…
1999	Frederick P. Brooks, Jr.	For landmark contributions to **computer architecture, operating systems, and software engineering**…
2000	Andrew Chi-Chih Yao	**Theory of computation**, pseudorandom number generation, cryptography, and communication complexity…
2001	Ole-Johan Dahl Kristen Nygaard	**Object-oriented programming**, Simula I and Simula 67…
2002	Ronald L. Rivest, Adi Shamir, Leonard M. Adleman	For their ingenious contribution for making **public-key cryptography** useful in practice.
2003	Alan Kay	Contemporary **object-oriented programming languages**…
2004	Vinton G. Cerf Robert E. Kahn	**Internetworking**, including the design and implementation of the Internet's basic communications protocols, TCP/IP…
2005	Peter Naur	**Programming language design**, ALGOL 60, compiler design…
2006	Frances E. Allen	**Optimizing compiler techniques**…

Turing Award Recipients (cont.)

2007	Edmund M. Clarke, E. Allen Emerson and Joseph Sifakis	For their roles in developing model checking into a **highly effective verification technology**, widely adopted in the hardware and software industries…
2008	Barbara Liskov	**Programming language and system design**…
2009	Charles P. Thacker	**Xerox Alto, the 1st modern PC, Ethernet and Tablet PC**….
2010	Leslie G. Valiant	Theory of computation…
2011	Judea Pearl	**Artificial intelligence** through the development of a calculus for **probabilistic and causal reasoning**…
2012	Silvio Micali Shafi Goldwasser	Transformative work that laid the complexity-theoretic foundations for the science of **cryptography**…
2013	Leslie Lamport	Contributed to **distributed and concurrent systems**…
2014	Michael Stonebraker	Concepts underlying **modern database systems**…
2015	Martin E. Hellman Whitfield Diffie	Introduced **public-key cryptography**, the foundation for the most regularly-used security protocols on the Internet…
2016	Tim Berners-Lee	Invented the **World Wide Web** and the **first web browser**…

Marvin Minsky

- Marvin Lee Minsky (August 9, 1927 – January 24, 2016) was an American cognitive scientist concerned largely with research of **artificial intelligence** (AI), co-founder of the Massachusetts Institute of Technology's AI laboratory, and author of several texts concerning AI and philosophy.
- Awards
  - **Turing Award (1969)**
  - Japan Prize (1990)
  - IJCAI Award for Research Excellence (1991)
  - Benjamin Franklin Medal (2001)
  - Computer History Museum Fellow (2006)
  - BBVA Foundation Frontiers of Knowledge Award (2013)

Logical vs. Analogical
or
Symbolic vs. Connectionist
or
Neat vs. Scruffy

https://web.media.mit.edu/~minsky/papers/SymbolicVs.Connectionist.html

Marvin Minsky

In Artificial Intelligence at MIT, Expanding Frontiers, Patrick H. Winston (Ed.), Vol.1, MIT Press, 1990. Reprinted in AI Magazine, Summer 1991.

Ensembles

"To solve really hard problems, we'll have to use *several different representations*…

It is time to *stop arguing* over *which* type of pattern-classification technique *is best*…

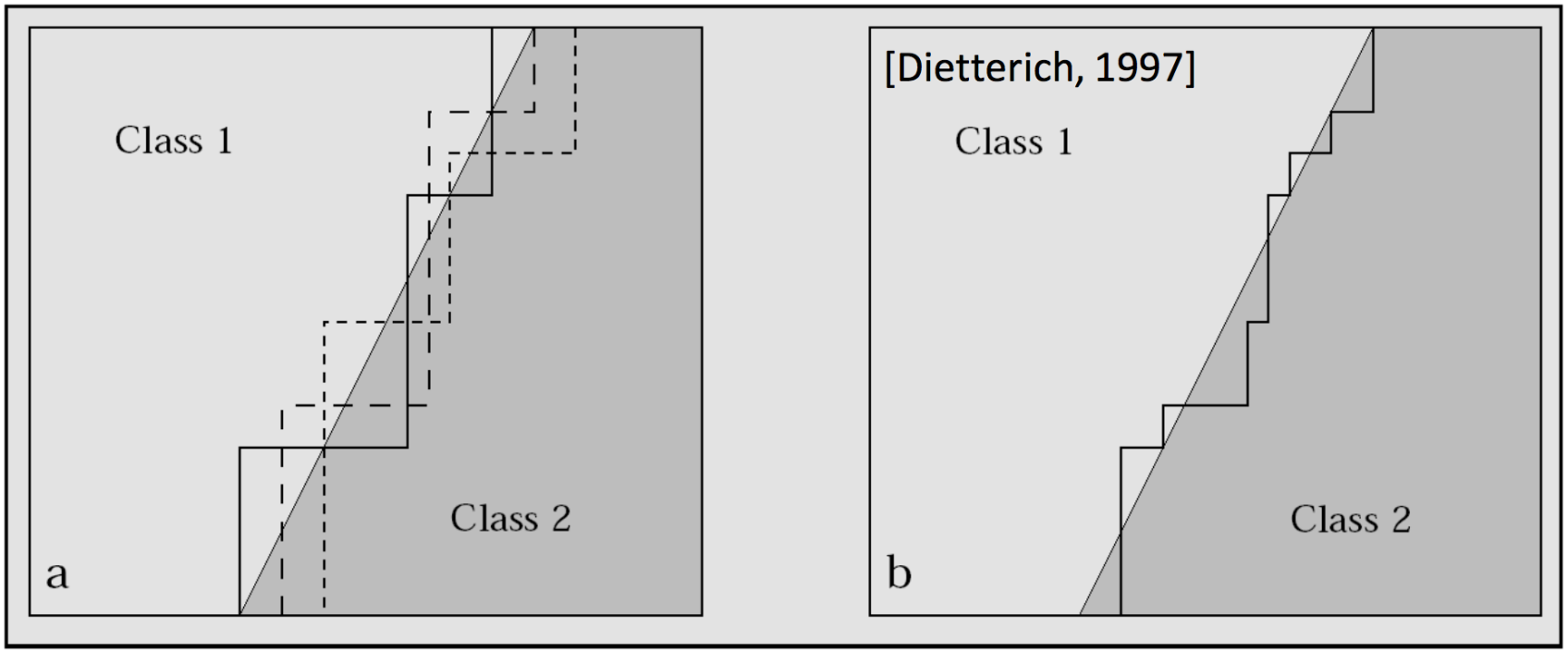
Instead we should work at a higher level of organization and discover how to build *managerial systems* to exploit the *different virtues* and evade the *different limitations* of each of these ways of comparing things." [**Minsky, 1991**]

Ensembles (cont.)

- An ensemble is a set of classifiers that learn a target function, and their *individual predictions are combined* (weighted or unweighted) to classify new examples
  - Each classifier should be *more accurate than by chance*, and independent of one another.
  - Usually *more accurate than a single classifier*.
- Ensembles generally improve the *generalization performance* of a set of classifiers on a domain.

Ensemble Methods

- Ensemble methods
  - Use a *combination of models* to ***increase accuracy***
  - Combine a series of *k* learned models, M_1, M_2, …, M_k, with the aim of creating an *improved model* M*



Ensemble Methods (cont.)

- Popular ensemble methods
  - **Bagging:** averaging the prediction over a collection of classifiers
  - **Boosting:** weighted vote with a collection of classifiers
    - **AdaBoost (Adaptive Boosting):** adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers.

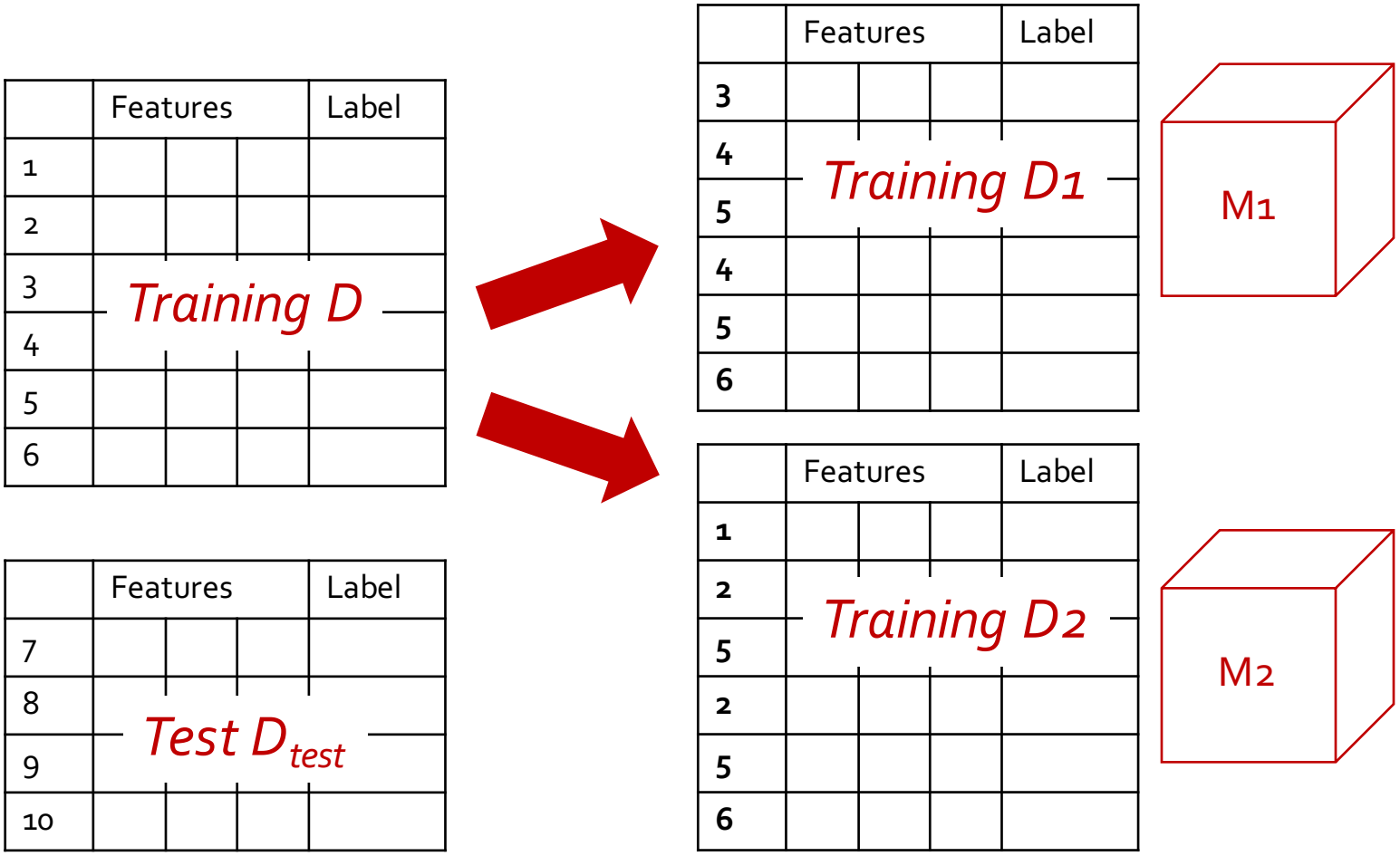
Bagging

- Training
  - Given a data set D of *d* instances, a classifier model M_i is learned for a training set D_i of *d* instances that is *sampled with replacement* from D (i = 1…k)
  - As a result of the *sampling-with-replacement* procedure, each classifier is trained on approximately *63.2%* of the training examples
  - For a dataset with *d* instances, each instance has a probability of $1 - (1 - 1/d)^d$ of being selected at least once in the *d* samples.
    - For $d \rightarrow \infty$, this number converges to $(1 - 1/e)$ or 0.632 [Bauer and Kohavi, 1999]

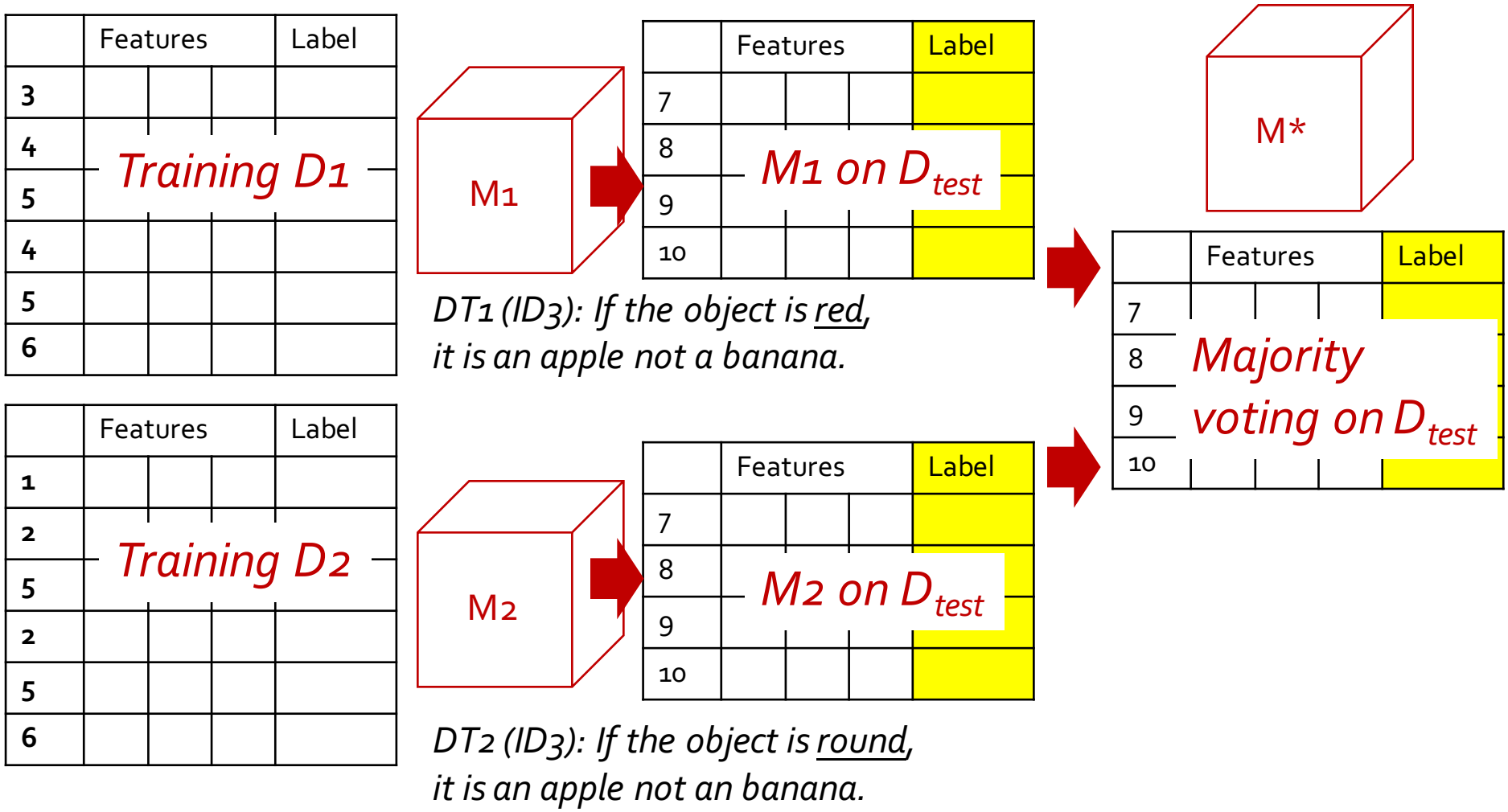
Bagging (cont.)

- Classification: classify an unknown sample **X**
  - Each classifier M_i returns its class prediction
  - The bagged classifier M* *counts the votes* and assigns the class with the *most votes* to **X**
- Accuracy: Proved improved accuracy in prediction
  - *Often significantly better* than a single classifier derived from D

Bagging (cont.)



Bagging (cont.)



Majority Voting

- *Example:* (Course Project) Entity type recognition
  - Features: Triggers in contextual words
    - The probability that the technical term is a "method" ("problem", "dataset", "metric", etc.).
  - Each context setting as a classifier: contextual words.

http://www.meng-jiang.com/teaching/TypingDemo.zip

Boosting

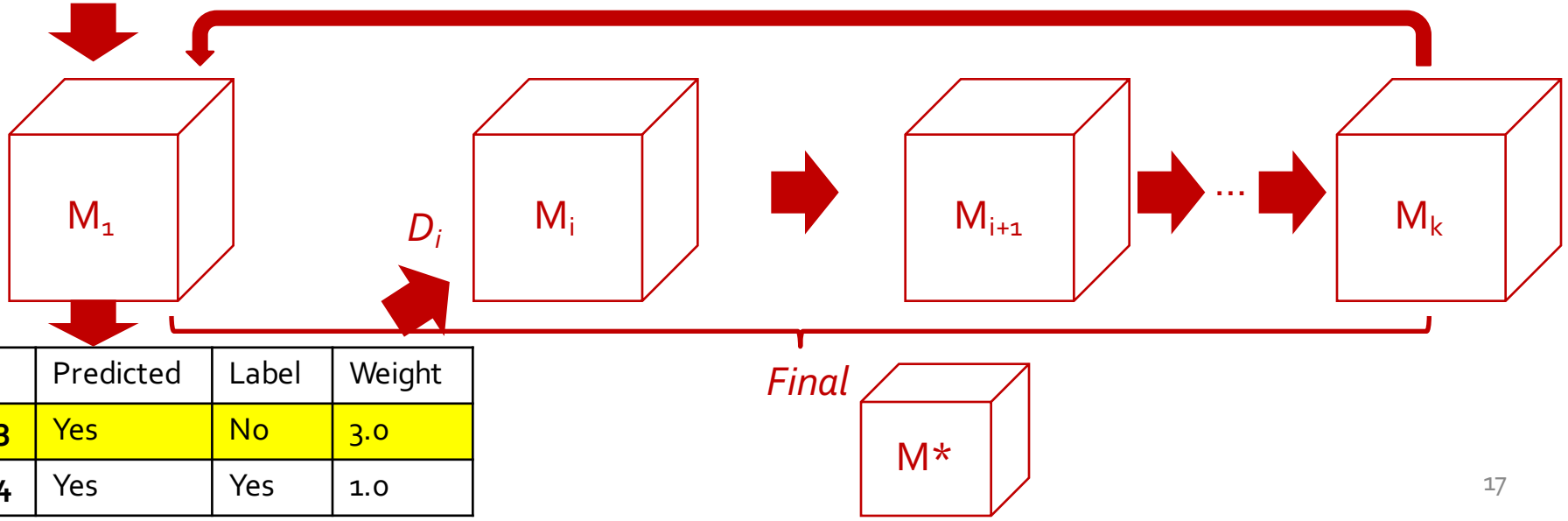
- Training
  - *Weights* are assigned to each training instance
  - A series of *k* classifiers is *iteratively* learned
  - After a classifier M_i is learned, the *weights* are updated to allow the subsequent classifier, M_{i+1}, to pay more attention to the *training* instances that were *misclassified* by M_i
- Classification
  - The final M* *combines the votes* of each individual classifier, where the *weight* of each classifier's vote is a function of its *accuracy* on classifying training instances
- Comparing with Bagging: Boosting tends to have *greater accuracy*, but it risks *overfitting* the model to misclassified data

	Features	Label	Weight
1			1.0
2	*Training D*		1.0
3			1.0
4			1.0
5			1.0
6			1.0

	Features	Label
3		
4	*Training D1*	
5		
4		
5		
6		

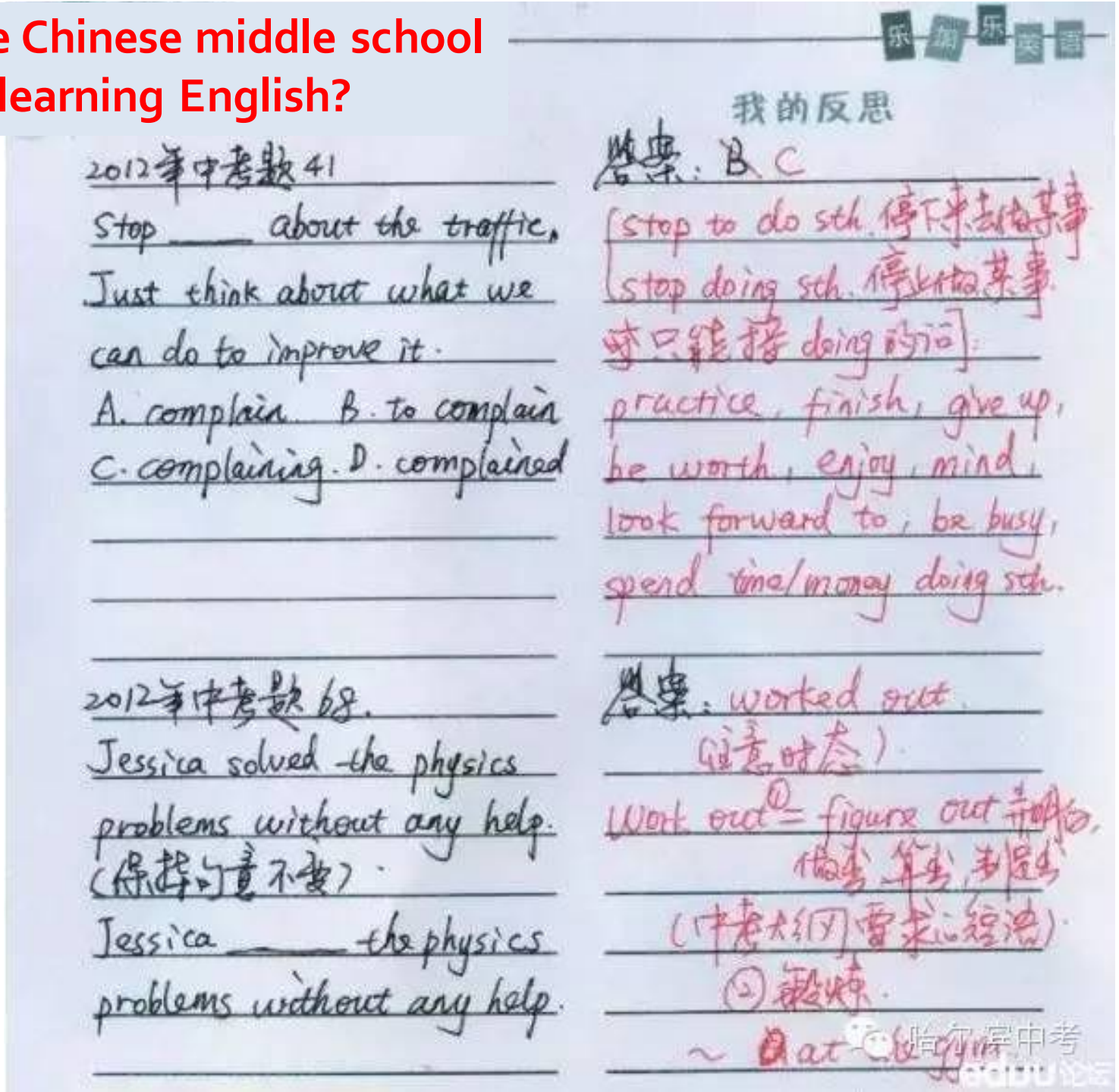
	Features	Label
3	*Training D_i*	
...		
...		...

Iteratively



	Predicted	Label	Weight
3	Yes	No	3.0
4	Yes	Yes	1.0

How were Chinese middle school students learning English?



我的反思

2012年中考题41

Stop ____ about the traffic. Just think about what we can do to improve it.

A. complain B. to complain C. complaining D. complained

答案：B C

[stop to do sth. 停下来去做某事
stop doing sth. 停止做某事
时只能接 doing 的话]

practice, finish, give up, be worth, enjoy, mind, look forward to, be busy, spend time/money doing sth.

2012年中考题68.

Jessica solved the physics problems without any help.
(保持句意不变)

Jessica ____ the physics problems without any help.

答案：worked out
(注意时态)

Work out ① = figure out 弄明白，
做出，算出，判定
(中考经常要求短语)
② 锻炼
~ at 在……

AdaBoost (Adaptive Boosting)

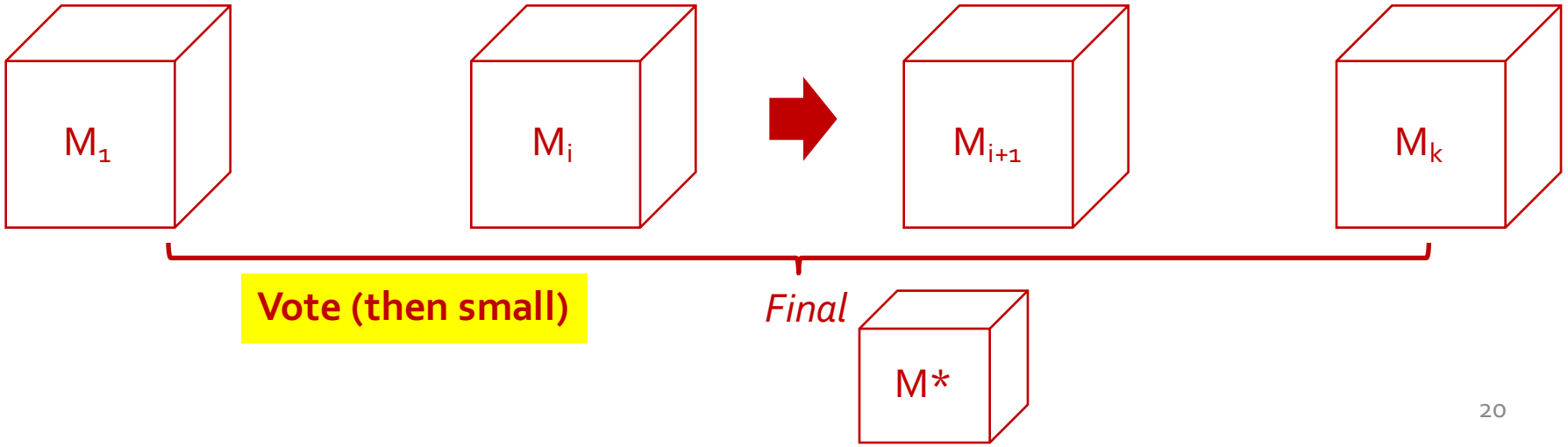
- Given a set of *d* class-labeled instances, ($\mathbf{X_1}$, y_1), …, ($\mathbf{X_d}$, y_d)
- Initially, all the *weights* of instances are set the same (1/*d*)
- Generate *k* classifiers in *k* rounds. At round *i*,
  - Instances from D are *sampled with replacement* to form a training set D_i of the same size
  - Each instance's chance of being selected is based on its *weight*
  - A classification model M_i is derived from D_i
  - Its *error rate* is calculated *using D_i as a "test set"*
  - If an instance is misclassified, its *weight* is increased, otherwise it is decreased

AdaBoost (cont.)

	Features			Label	Weight
1					1.0
2		*Training D*			1.0
3					1.0
4					1.0
5					1.0
6					1.0

	Features			Label	Weight
1					3.0
2					2.1
3					0.5
4					1.5
5					1.0
6					1.0

Error rate (if high)



Is  a fish?

AdaBoost (cont.)

- *Error rate:* *err($\mathbf{X}_j$)* is the misclassification error of instance $\mathbf{X}_j$. Classifier M_i's error rate is the sum of the weights of the misclassified instances:

$$error(M_i) = \sum_j^d w_j \times err(\mathbf{X_j})$$

- The *weight* of classifier M_i's vote is

$$\log \frac{1 - error(M_i)}{error(M_i)}$$

Summary

- Ensembles
- Bagging
- Boosting
  - AdaBoost

An Example

"SetExpan: Corpus-Based Set Expansion via Context Feature Selection and Rank Ensemble"

by Shen et al. at UIUC

Macedonia


France
Switzerland
Austria
Budapest
Hungary
Moldova
Chisinau
Odessa
Одеса
Milan
Slovenia
Zagreb
Romania
Belgrade
Београд
Croatia
Bucharest
Bosnia and
Herzegovina
Serbia
Monaco
Sarajevo
Sofia
София
Black Sea
Italy
Andorra
Podgorica
Подгорица
Kosovo
Bulgaria
Barcelona
Rome
Macedonia
(FYROM)
Tirana
Albania
Istanbul
Bursa
Ankara
Tyrrhenian Sea
Greece
Turkey
Athens
Αθήνα
Izmir
Algiers
مدينة الجزائر
Tunis
تونس
Antalya
Adana
Malta

Skopje

An Example (cont.)

"**SetExpan: Corpus-Based Set Expansion via Context Feature Selection and Rank Ensemble**"

by Shen et al. at UIUC

http://mickeystroller.github.io/resources/ECMLPKDD2017.pdf

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