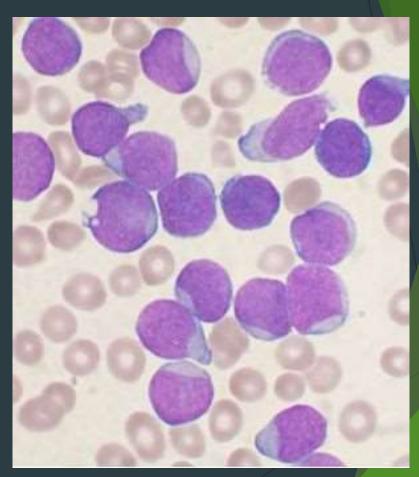


What is Leukemia?



Wikipedia

#### The Data - GSE13159

- ▶ Name: Microarray Innovations in LEukemia (MILE) study: Stage 1 data
  - ▶ Data collected from 11 centers across 3 continents
  - ► Size: ~616 MB
  - ▶ Data released on Sept 30, 2009
- ▶ n = 2096 patients
- ▶ d = 17,788 genes
- ▶ 18 classes

#### Data breakdown

Name	Count
MDS	207
CLL	448
AML complex aberrant karyotype	52
AML with normal karyotype + other abnormalities	347
c-ALL/Pre-B-ALL without t(9;22)	237
T-ALL	174
CML	76
AML with t(11q23)/MLL	38
ALL with t(12;21)	58

Name	Count
Non-leukemia and healthy bone marrow	73
c-ALL/Pre-B-ALL with t(9;22)	122
AML with t(8;21)	40
ALL with hyperdiploid karyotype	40
ALL with t(1;19)	36
Pro-B-ALL with t(11q23)/MLL	70
AML with t(15;17)	37
AML with inv(16)/t(16;16)	28
mature B-ALL with t(8;14)	13

#### Goal

Understand how gene expression patterns are different in different subtypes of leukemia

#### Challenges:

- Interpreting results
- Determining significance of results
- (I didn't know we had to do a presentation until last week)



#### Approach

- 90/10 train/test split
- Finding significant features among different leukemia subtypes
  - ► Check for significant features (applying Bonferroni correction)
  - ▶ Look at most common significant features
- Logistic Regression
  - Check with all features/only with significant features and different data normalization methods
  - ▶ Check similarity between learned weights
  - Analyze learned weights
- K-Nearest Neighbors

#### Finding significant features

- Bonferroni correction (p=0.05, m=17788)
  - ▶ Performed on training set
  - "Non-leukemia and healthy bone marrow" vs. others
- ▶ 1,408 significant features in total

Leukemia sub-type	Number of significant features			
MDS	39			
CLL	956			
AML complex aberrant karyotype	220			
AML with normal karyotype + other abnormalities	522			

	A.
Leukemia sub-type (cont.)	Number of significant features
c-ALL/Pre-B-ALL without t(9;22)	817
T-ALL	793
CML	195
AML with t(11q23)/MLL	271
ALL with t(12;21)	724
c-ALL/Pre-B-ALL with t(9;22)	731
AML with t(8;21)	373
ALL with hyperdiploid karyotype	581
ALL with t(1;19)	612
Pro-B-ALL with t(11q23)/MLL	689
AML with t(15;17)	428
AML with inv(16)/t(16;16)	351
mature B-ALL with t(8;14)	48

### Jaccard similarity of significant features

J(A, B	$) = \frac{ A \cap B }{ A \cup B }$	MDS	CLL	AML complex aberrant karyotype	AML with normal karyotype + other abnormalities	c-ALL/Pre-B-ALL without t(9;22)	T-ALL	CML	AML with t(11q23)/MLL	ALL with t(12;21)	c-ALL/Pre-B-ALL with t(9;22)	AML with t(8;21)	ALL with hyperdiploid karyotype	ALL with t(1;19)	Pro-B-ALL with t(11q23)/MLL	AML with t(15;17)	AML with inv(16)/t(16;16)	mature B-ALL with t(8;14)
	MDS	1.00	0.03	0.07	0.04	0.04	0.03	0.03	0.05	0.04	0.04	0.05	0.05	0.04	0.04	0.06	0.04	0.00
	CLL	0.03	1.00	0.17	0.37	0.53	0.49	0.14	0.20	0.44	0.47	0.28	0.38	0.39	0.46	0.31	0.26	0.04
	AML complex aberrant karyotype	0.07	0.17	1.00	0.28	0.19	0.19	0.11	0.16	0.18	0.19	0.25	0.19	0.18	0.19	0.21	0.22	0.06
	AML with normal karyotype + other abnormalities	0.04	0.37	0.28	1.00	0.44	0.40	0.15	0.37	0.34	0.40	0.44	0.35	0.37	0.45	0.41	0.43	0.06
	c-ALL/Pre-B-ALL without t(9;22)	0.04	0.53	0.19	0.44	1.00	0.58	0.14	0.22	0.62	0.70	0.33	0.56	0.55	0.60	0.34	0.31	0.05
	T-ALL	0.03	0.49	0.19	0.40	0.58	1.00	0.15	0.21	0.50	0.52	0.31	0.43	0.47	0.51	0.33	0.27	0.05
	CML	0.03	0.14	0.11	0.15	0.14	0.15	1.00	0.16	0.17	0.15	0.16	0.15	0.17	0.16	0.16	0.16	0.05
	AML with t(11q23)/MLL	0.05	0.20	0.16	0.37	0.22	0.21	0.16	1.00	0.19	0.23	0.33	0.21	0.21	0.25	0.28	0.34	0.09
	ALL with t(12;21)	0.04	0.44	0.18	0.34	0.62	0.50	0.17	0.19	1.00	0.54	0.28	0.54	0.53	0.48	0.33	0.28	0.04
	c-ALL/Pre-B-ALL with t(9;22)	0.04	0.47	0.19	0.40	0.70	0.52	0.15	0.23	0.54	1.00	0.33	0.52	0.51	0.53	0.34	0.31	0.05
	AML with t(8;21)	0.05	0.28	0.25	0.44	0.33	0.31	0.16	0.33	0.28	0.33	1.00	0.28	0.30	0.35	0.40	0.41	0.07
	ALL with hyperdiploid karyotype	0.05	0.38	0.19	0.35	0.56	0.43	0.15	0.21	0.54	0.52	0.28	1.00	0.49	0.48	0.32	0.30	0.05
	ALL with t(1;19)	0.04	0.39	0.18	0.37	0.55	0.47	0.17	0.21	0.53	0.51	0.30	0.49	1.00	0.53	0.31	0.31	0.05
	Pro-B-ALL with t(11q23)/MLL	0.04	0.46	0.19	0.45	0.60	0.51	0.16	0.25	0.48	0.53	0.35	0.48	0.53	1.00	0.36	0.32	0.05
	AML with t(15;17)	0.06	0.31	0.21	0.41	0.34	0.33	0.16	0.28	0.33	0.34	0.40	0.32	0.31	0.36	1.00	0.32	0.06
	AML with inv(16)/t(16;16)	0.04	0.26	0.22	0.43	0.31	0.27	0.16	0.34	0.28	0.31	0.41	0.30	0.31	0.32	0.32	1.00	0.07
	mature B-ALL with t(8;14)	0.00	0.04	0.06	0.06	0.05	0.05	0.05	0.09	0.04	0.05	0.07	0.05	0.05	0.05	0.06	0.07	1.00

# Checking the common significant features

# shared labels	# genes
16	1
15	17
14	31
13	30
12	51
11	64
10	75
9	110
8	101
7	128
6	111
5	103
4	116
3	125
2	130
1	215

# shared labels	Name of gene
16	10487_at
15	1116_at
15	116362_at
15	10123_at
15	1118_at
15	10562_at

<sup>\*</sup> We have information on which labels the gene is shared by, but it wouldn't fit on the slide.

# Example: Looking at the most common significant gene

#### Shared by:

CLL, AML complex aberrant karyotype, AML with normal karyotype + other abnormalities, c-ALL/Pre-B-ALL without t(9;22), T-ALL, CML, AML with t(11q23)/MLL, ALL with t(12;21), c-ALL/Pre-B-ALL with t(9;22), AML with t(8;21), ALL with hyperdiploid karyotype, ALL with t(1;19), Pro-B-ALL with t(11q23)/MLL, AML with t(15;17), AML with inv(16)/t(16;16), mature B-ALL with t(8;14)

Not shared by: MDS

Gene: 10487\_at

Shared by: 16 leukemia subtypes

Description: CAP1 - CAP, adenylate cyclase-

associated protein 1 (yeast)

#### Checking significance

Gene: 10487\_at

Shared by: 16 leukemia types

Description: CAP1 - CAP, adenylate cyclase-associated protein 1 (yeast)

From [Xie, Shen, Tan, Li, Song, Wang 2017]: "CAP1 [...] was under-expressed in breast and leukemia cancers as compared to that in normal tissue."



#### Learning settings

- Used 5-fold cross validation
- ▶ L1 regularization
- ▶ With all features vs. with significant features
- ▶ Different normalization schemes
- ▶ 1 vs. all classification scheme

#### Normalization schemes

- Don't normalize
- Normalize across entire training dataset
- Normalize by healthy patient data in training dataset

#### Results of 5-fold cross-validation

Normalization Scheme	w/ all fo	eatures	w/ significant features		
Normanzation Scheme	Top 1 acc. Top 5 acc.		Top 1 acc.	Top 5 acc.	
Don't normalize	0.895	0.995	0.870	0.987	
Normalize across entire training dataset	0.898	0.988	0.881	0.986	
Normalize by healthy patient data in training dataset	0.907	0.991	0.884	0.984	

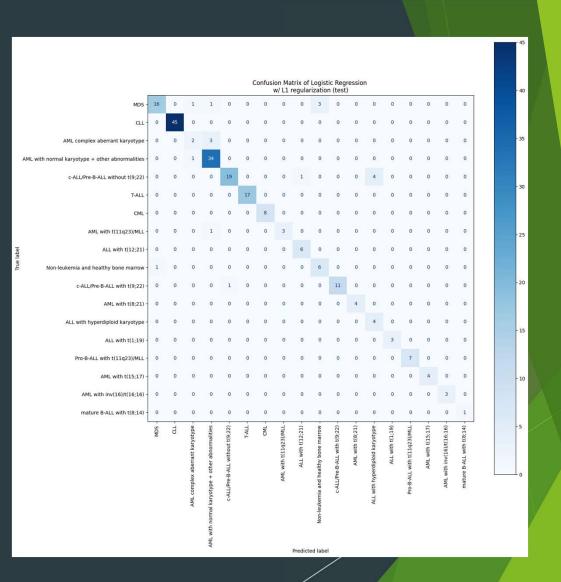
#### Results

Train

Normalization Scheme	w/ all fo	eatures	w/ significant features		
Normalization Scheme	Top 1 acc. Top 5 acc.		Top 1 acc.	Top 5 acc.	
Don't normalize	1.0	1.0	1.0	1.0	
Normalize across entire training dataset	1.0	1.0	1.0	1.0	
Normalize by healthy patient data in training dataset	1.0	1.0	1.0	1.0	

Test

Normalization Scheme	w/ all f	eatures	w/ significant features		
Normanzacion Scheme	Top 1 acc.	Top 5 acc.	Top 1 acc.	Top 5 acc.	
Don't normalize	0.919	1.0	0.881	0.990	
Normalize across entire training dataset	0.919	0.995	0.857	0.981	
Normalize by healthy patient data in training dataset	0.900	0.995	0.843	0.971	



#### Reflecting on results

\* results from using all features and no normalization

## Features used by leukemia sub-type model

Leukemia Sub-type	# zeros	# non-zero
MDS	15400	2388
CLL	17004	784
AML complex aberrant karyotype	17258	530
AML with normal karyotype + other abnormalities	15227	2561
c-ALL/Pre-B-ALL without t(9;22)	15381	2407
T-ALL	16507	1281
CML	17040	748
AML with t(11q23)/MLL	17080	708
ALL with t(12;21)	17072	716

	Y .	/ /
Leukemia Sub-type	# zeros	# non-zero
Non-leukemia and healthy bone marrow	17235	553
c-ALL/Pre-B-ALL with t(9;22)	16414	1374
AML with t(8;21)	17336	452
ALL with hyperdiploid karyotype	16999	789
ALL with t(1;19)	17132	656
Pro-B-ALL with t(11q23)/MLL	16959	829
AML with t(15;17)	17202	586
AML with inv(16)/t(16;16)	17481	307
mature B-ALL with t(8;14)	17544	244

Total number of genes: 17788

#### Cosine Similarity to compare learned weights

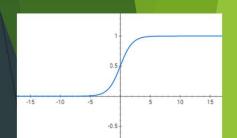
C(A B)	_	$A \cdot B$				
C(A,D)		$\frac{11 - B}{\ A\  \times \ B\ }$				

\* results from using all features and no normalization

2	$ A   \times   B  $	MDS	TID	AML comp aberrant kar	AML with normal + other abnor	c-ALL/Pre- without t(	T-ALL	CML	AML with t(110	ALL with t(	Non-leukem healthy bone	c-ALL/Pre-I with t(9;	AML with to	ALL wit hyperdiploid k	ALL with t(	Pro-B-ALL t	AML with t(	AML with inv(16	mature B-ALL w
	MDS	1.000	-0.002	-0.034	-0.145	0.006	-0.010	-0.065	-0.013	-0.037	-0.206	-0.017	-0.024	0.016	0.012	-0.011	-0.015	-0.018	0.022
	CLL	-0.002	1.000	-0.024	-0.029	-0.028	-0.016	0.007	-0.017	-0.002	-0.007	0.009	0.023	-0.015	0.001	0.004	0.015	-0.013	-0.021
	AML complex aberrant karyotype	-0.034	-0.024	1.000	-0.122	-0.012	-0.001	-0.011	0.001	-0.006	-0.037	-0.021	0.022	0.016	0.006	0.010	-0.004	0.020	-0.004
Δ	ML with normal karyotype + other abnormalities	-0.145	-0.029	-0.122	1.000	-0.028	-0.058	-0.070	-0.104	-0.009	-0.049	0.004	-0.062	-0.016	0.000	-0.016	-0.021	-0.064	-0.009
	c-ALL/Pre-B-ALL without t(9;22)	0.006	-0.028	-0.012	-0.028	1.000	-0.012	-0.019	-0.001	-0.126	0.005	-0.207	-0.008	-0.109	-0.050	-0.026	0.021	-0.007	-0.006
	T-ALL	-0.010	-0.016	-0.001	-0.058	-0.012	1.000	0.010	-0.004	-0.014	-0.003	-0.018	-0.009	-0.006	-0.001	-0.015	-0.012	0.018	0.012
	CML	-0.065	0.007	-0.011	-0.070	-0.019	0.010	1.000	-0.007	-0.004	-0.014	0.007	-0.008	-0.026	0.007	0.011	-0.049	-0.029	-0.010
	AML with t(11q23)/MLL	-0.013	-0.017	0.001	-0.104	-0.001	-0.004	-0.007	1.000	0.011	-0.008	0.000	0.001	-0.011	0.007	0.018	-0.011	0.024	-0.003
	ALL with t(12;21)	-0.037	-0.002	-0.006	-0.009	-0.126	-0.014	-0.004	0.011	1.000	0.021	-0.025	0.008	-0.026	-0.018	-0.026	0.000	-0.001	0.003
	Non-leukemia and healthy bone marrow	-0.206	-0.007	-0.037	-0.049	0.005	-0.003	-0.014	-0.008	0.021	1.000	-0.008	-0.004	0.017	-0.012	0.012	-0.006	0.012	0.007
ı	c-ALL/Pre-B-ALL with t(9;22)	-0.017	0.009	-0.021	0.004	-0.207	-0.018	0.007	0.000	-0.025	-0.008	1.000	0.018	-0.019	-0.022	-0.030	-0.021	0.005	-0.008
	AML with t(8;21)	-0.024	0.023	0.022	-0.062	-0.008	-0.009	-0.008	0.001	0.008	-0.004	0.018	1.000	-0.005	-0.002	-0.012	0.016	0.009	-0.014
ı	ALL with hyperdiploid karyotype	0.016	-0.015	0.016	-0.016	-0.109	-0.006	-0.026	-0.011	-0.026	0.017	-0.019	-0.005	1.000	-0.013	-0.004	0.022	0.002	0.011
	ALL with t(1;19)	0.012	0.001	0.006	0.000	-0.050	-0.001	0.007	0.007	-0.018	-0.012	-0.022	-0.002	-0.013	1.000	-0.019	0.005	0.008	0.006
ı	Pro-B-ALL with t(11q23)/MLL	-0.011	0.004	0.010	-0.016	-0.026	-0.015	0.011	0.018	-0.026	0.012	-0.030	-0.012	-0.004	-0.019	1.000	-0.002	0.005	0.010
	AML with t(15;17)	-0.015	0.015	-0.004	-0.021	0.021	-0.012	-0.049	-0.011	0.000	-0.006	-0.021	0.016	0.022	0.005	-0.002	1.000	0.011	-0.001
	AML with inv(16)/t(16;16)	-0.018	-0.013	0.020	-0.064	-0.007	0.018	-0.029	0.024	-0.001	0.012	0.005	0.009	0.002	0.008	0.005	0.011	1.000	0.020
	mature B-ALL with t(8;14)	0.022	-0.021	-0.004	-0.009	-0.006	0.012	-0.010	-0.003	0.003	0.007	-0.008	-0.014	0.011	0.006	0.010	-0.001	0.020	1.000

#### Most heavily weighted weights

\* results from using all features and no normalization



•••

MDS

CCL

Н	ig	hest
	-	

Name	Coefficient				
66000_at	0.100164				
2706_at	0.091647				
158809_at	0.088469				
100130703_at	0.083912				
9518_at	0.083138				

Name	Coefficient
27033_at	0.079577
130367_at	0.067018
5923_at	0.052974
81537_at	0.043758
2823_at	0.041918

•••

Lowest

Name	Coefficient					
285299_at	-0.073488877					
388951_at	-0.074094855					
51673_at	-0.079185137					
7266_at	-0.144620158					
56884_at	-0.205755898					

•••

Name	Coefficient
79872_at	-0.04386
100131644_at	-0.04524
85358_at	-0.04816
390058_at	-0.11016
3892_at	-0.16053

#### K-Nearest Neighbors

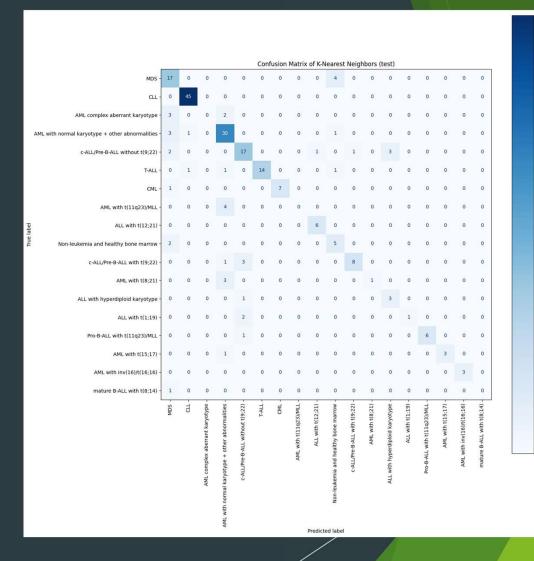
Instance-based learning

Parameters to tune:

- ► K, i.e. # of neighbors
  - n = 2096 patients
- Whether to use significant features or all the features

#### Results

# of	w/ all f	eatures	w/ significant features				
neighbors	Top 1 acc.	Top 5 acc.	Top 1 acc.	Top 5 acc.			
3	0.767	0.881	0.790	0.895			
5	0.771	0.914	0.790	0.929			
10	0.795	0.962	0.819	0.962			
15	0.786	0.967	0.819	0.952			
20	0.790	0.971	0.786	0.952			



#### Reflecting on results

► Similar results, but more different errors

#### **Future Work**

- Further examine and interpret the results and errors obtained
- ▶ Alternative 1 vs. all classification
  - Make a separate model for each leukemia subtype made by selecting out and training on the significant features
- ► Try different regularizers and machine learning methods
- Address data imbalance

#### Conclusion

- Analyzing shared significant features seems to be useful
- ▶ Logistic regression models can get close to 100% accuracy with MILE dataset
- ► K-Nearest Neighbors is okay, but not that great



