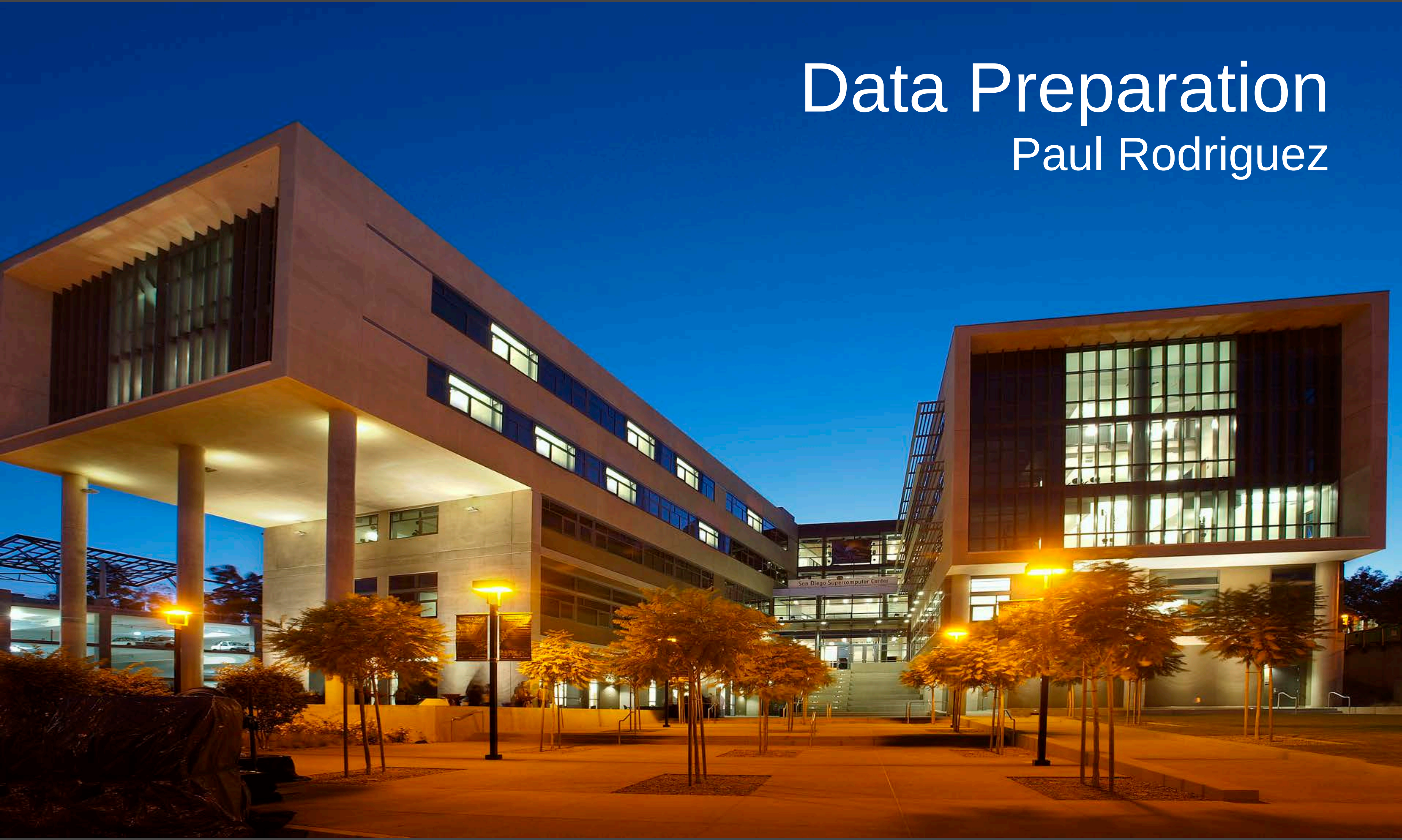
Data Preparation

Paul Rodriguez



On the Importance of Data Prep

- “Garbage in, garbage out”
- Sometimes takes 60-80% of the whole data mining effort

Working definition

- **Data Preparation:**
  - Cleaning
  - Filtering
  - Transforming
  - Organizing the data matrix (aka ‘data wrangling’ or ‘data munging’)
  - Variable Selection/Dimension Reduction

In a nutshell, know your variables and prepare data for modeling

Missing Data (NA vs NULL)

- **Not applicable - NA**

    e.g. spouse name depends on marital status

- **Not available - NULL**

    unknown

    not entered

- **In R:**

    NA is logically missing (ie the value won't be available)

    NULL is object not yet defined (ie the object is not available)

Missing Data

- **What are frequency counts of missing variables?**

    Are entries missing completely at random or contingent on some other variable?

Quick Approaches

- Delete instances

and/or

- Delete attributes with high missing-ness

Simple Imputation

- Use the attribute mean
- Use the attribute mean for each class label

Complicated Imputation

- **Use a model (based on other attributes) to infer missing value**

Complicated Imputation

- Use a model (based on other attributes) to infer missing value

Best strategy depends on

time vs accuracy tradeoffs

R and missing data

- **Several packages, such as ‘mice’ , ‘amelia’**
- **Produces multiple data sets**
- **Iterates over missing data estimates and linear model estimates**

  Mice uses Gibbs sampling (slower)

  Amelia uses Expectation Maximization (faster)
- **Beware of correlation in variables**

  Matrices not invertible

R and missing data

- **'Amelia' package example**
  - 50 attributes from UN voting data
  - 1K-100K entries missing per col for about 20 cols
  - 300K rows ~ 1 hour on compute node (not run on the user's PC)

time variable for time series models

cross section to select temporal periods

ignore 'id' variables

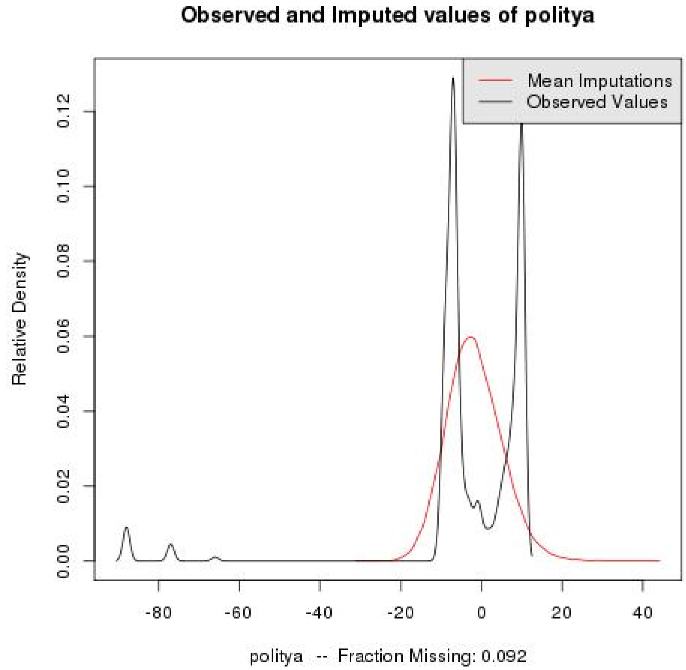
```
# run the imputation
library(‘amelia’)
 a.out <- amelia(data, ts = "year", cs = "dyadid",
               idvars = c("dyadidyr", "cntryera", "statea", "stateb"),
               intercs=FALSE, p2s = 2, m=10, parallel = "multicore”)
```

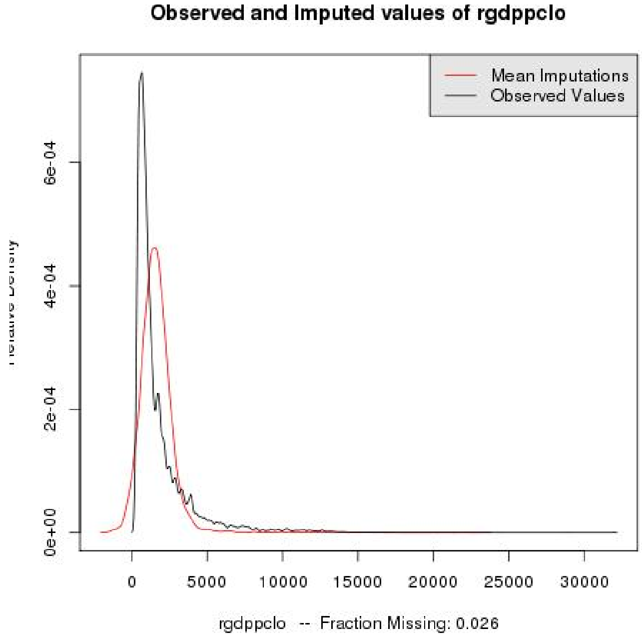
interactions

parallel options

R and missing data

#QA on missing data by comparing density of imputated & original data
compare.density(a.out, var=“politya")
compare.density(a.out,var='rgdpcontg')

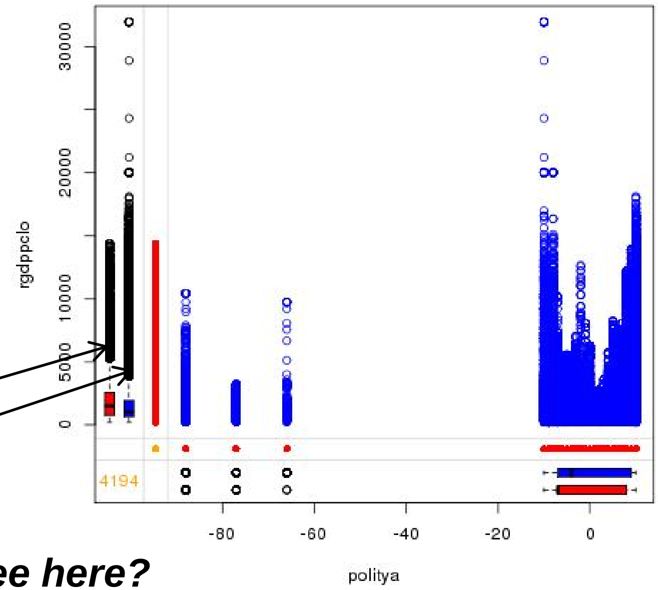




R and missing data

```
# Useful library for printing margin plots, to compare histograms
#                         conditional on missing/non-missing data
library('VIM')
marginplot(gart2use[,c('politya', 'rgdppclo')],
  col=c('blue','red','orange')
```

dist of rgdppclo when
politya missing
politya present



What would you want to see here?

Variable Transformations

- **Engineer new features**
- **Combine attributes**
  e.g. rates and ratios
- **Normalize or Scale data**
- **Discretize data**
  (perhaps more intuitive to deal with binned data)

Feature Engineering is Variable Enhancement

- **Use Domain and world knowledge**

- **Example: given date and location of doctor visits**

  a new variable for Number-of-1st-time-visits

  deduce a new variable for Number-of-visits-over-25-miles

  deduce a new variable for Amount-of-time-between-visits

Re-scaling

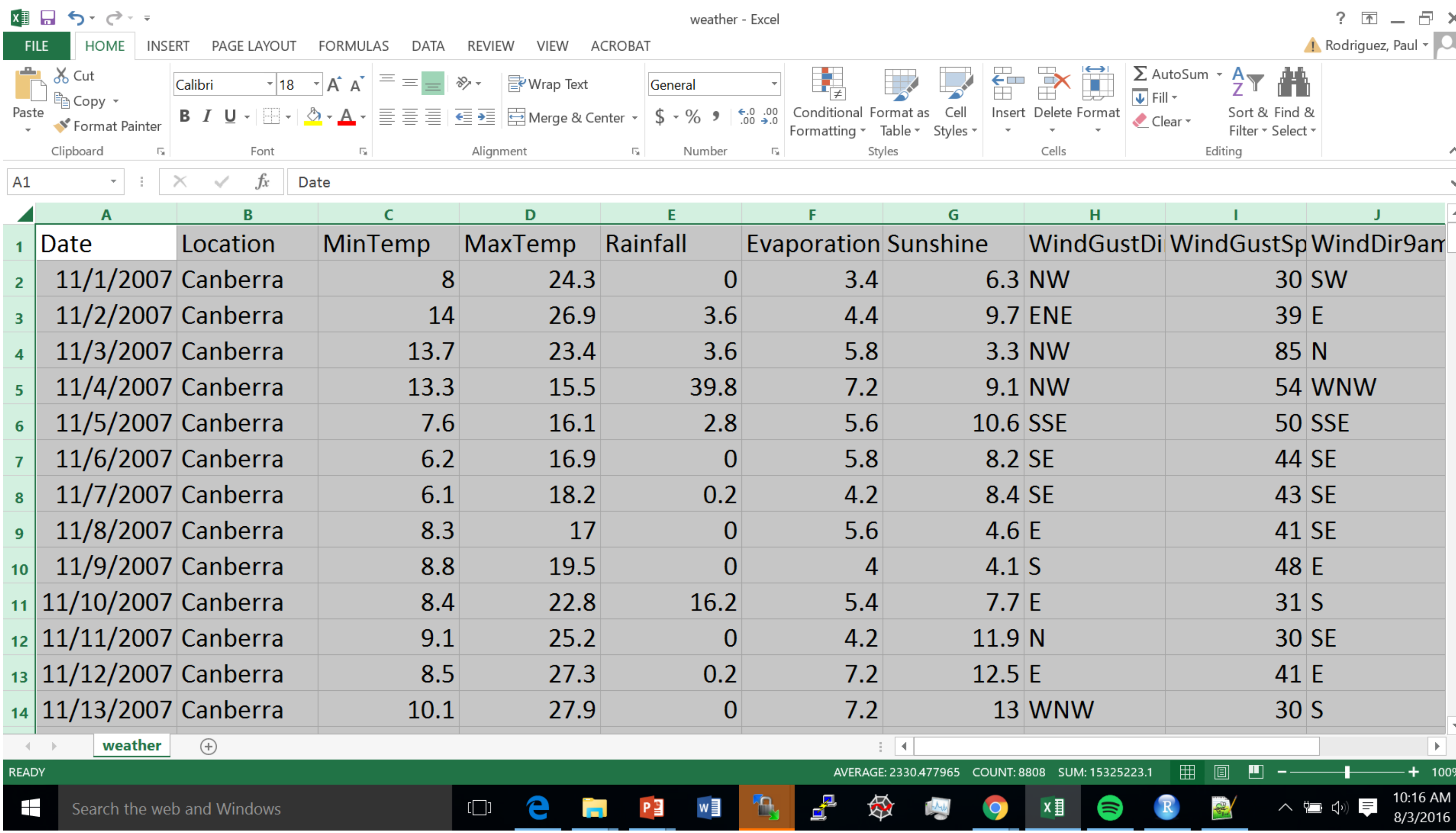
- **Mean center** $x_{new} = x - \mathrm{mean}(x)$
- **z-score** $$score = \frac{x - \mathrm{mean}(x)}{\mathrm{std}(x)}$$
- **Scale to [0…1]** $$x_{new} = \frac{x - \min(x)}{\max(x) - \min(x)}$$
- **log scaling** $x_{new} = \log(x)$

Generally

- Preparing data is based on statistical principles,

- But also heuristics

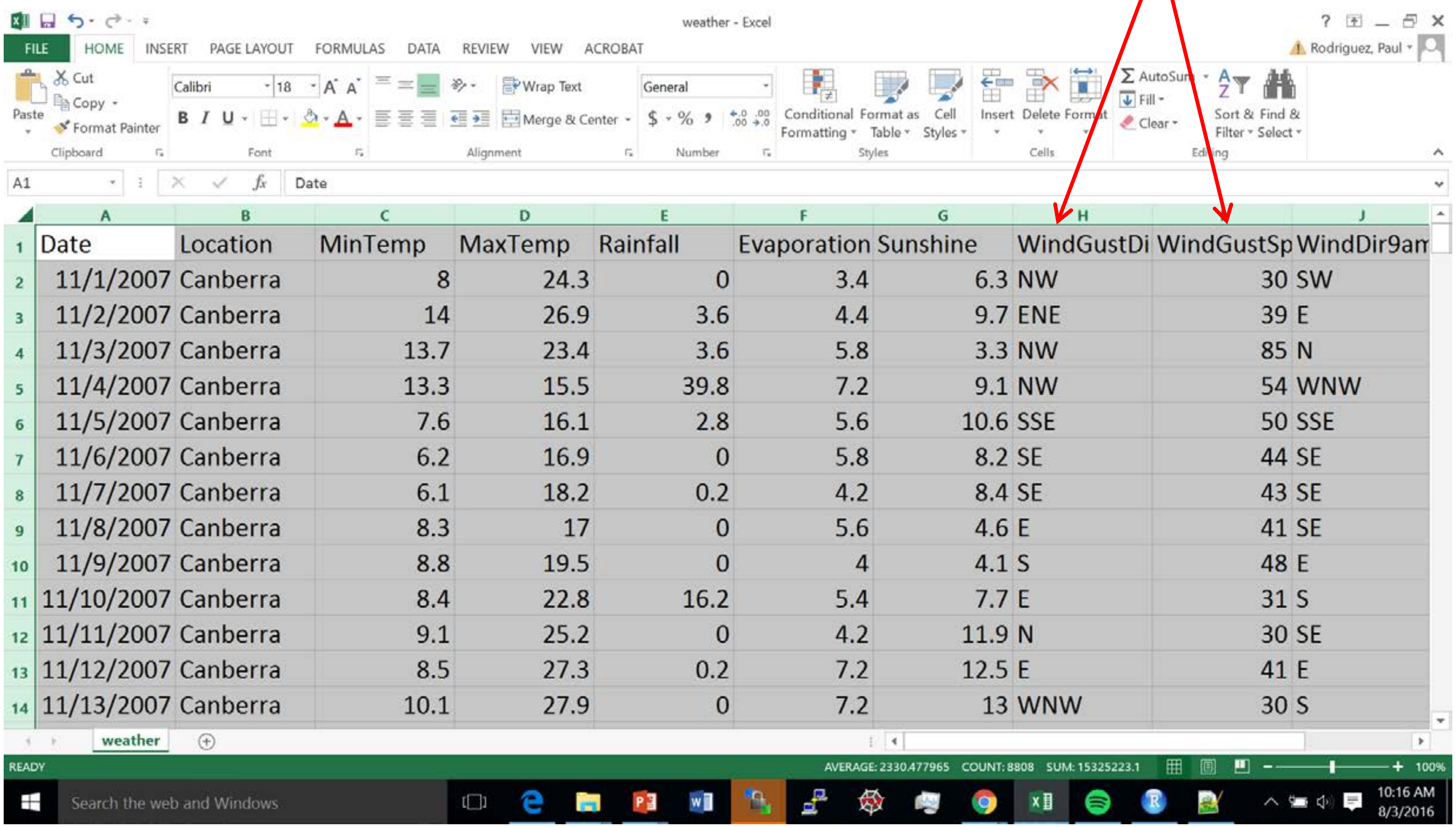
Data Wrangling Exercise: Weather Data



Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDi	WindGustSp	WindDir9am
11/1/2007	Canberra	8	24.3	0	3.4	6.3	NW	30	SW
11/2/2007	Canberra	14	26.9	3.6	4.4	9.7	ENE	39	E
11/3/2007	Canberra	13.7	23.4	3.6	5.8	3.3	NW	85	N
11/4/2007	Canberra	13.3	15.5	39.8	7.2	9.1	NW	54	WNW
11/5/2007	Canberra	7.6	16.1	2.8	5.6	10.6	SSE	50	SSE
11/6/2007	Canberra	6.2	16.9	0	5.8	8.2	SE	44	SE
11/7/2007	Canberra	6.1	18.2	0.2	4.2	8.4	SE	43	SE
11/8/2007	Canberra	8.3	17	0	5.6	4.6	E	41	SE
11/9/2007	Canberra	8.8	19.5	0	4	4.1	S	48	E
11/10/2007	Canberra	8.4	22.8	16.2	5.4	7.7	E	31	S
11/11/2007	Canberra	9.1	25.2	0	4.2	11.9	N	30	SE
11/12/2007	Canberra	8.5	27.3	0.2	7.2	12.5	E	41	E
11/13/2007	Canberra	10.1	27.9	0	7.2	13	WNW	30	S

Transforming Weather Data Matrix

Let's consider WindGustDir as a repeated measurement
Do we want that all in one row? Or in their own row?
- depends on the analysis



Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDi	WindGustSp	WindDir9am
11/1/2007	Canberra	8	24.3	0	3.4	6.3	NW	30	SW
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11/4/2007	Canberra	13.3	15.5	39.8	7.2	9.1	NW	54	WNW
11/5/2007	Canberra	7.6	16.1	2.8	5.6	10.6	SSE	50	SSE
11/6/2007	Canberra	6.2	16.9	0	5.8	8.2	SE	44	SE
11/7/2007	Canberra	6.1	18.2	0.2	4.2	8.4	SE	43	SE
11/8/2007	Canberra	8.3	17	0	5.6	4.6	E	41	SE
11/9/2007	Canberra	8.8	19.5	0	4	4.1	S	48	E
11/10/2007	Canberra	8.4	22.8	16.2	5.4	7.7	E	31	S
11/11/2007	Canberra	9.1	25.2	0	4.2	11.9	N	30	SE
11/12/2007	Canberra	8.5	27.3	0.2	7.2	12.5	E	41	E
11/13/2007	Canberra	10.1	27.9	0	7.2	13	WNW	30	S

Data Wrangling exercise

```
#Read in data:
W_df = read.table('weather.csv',
                  header=TRUE,
                        sep=",",
                  stringsAsFactors = TRUE)
```

Long to Wide transform

Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDi	WindGustSp	WindDir9am
11/1/2007	Canberra	8	24.3	0	3.4	6.3	NW	30	SW
11/2/2007	Canberra	14	26.9	3.6	4.4	9.7	ENE	39	E
11/3/2007	Canberra	13.7	23.4	3.6	5.8	3.3	NW	85	N

date, location and the rest identify the row

WindGustDir entries are labels for the repeated measures

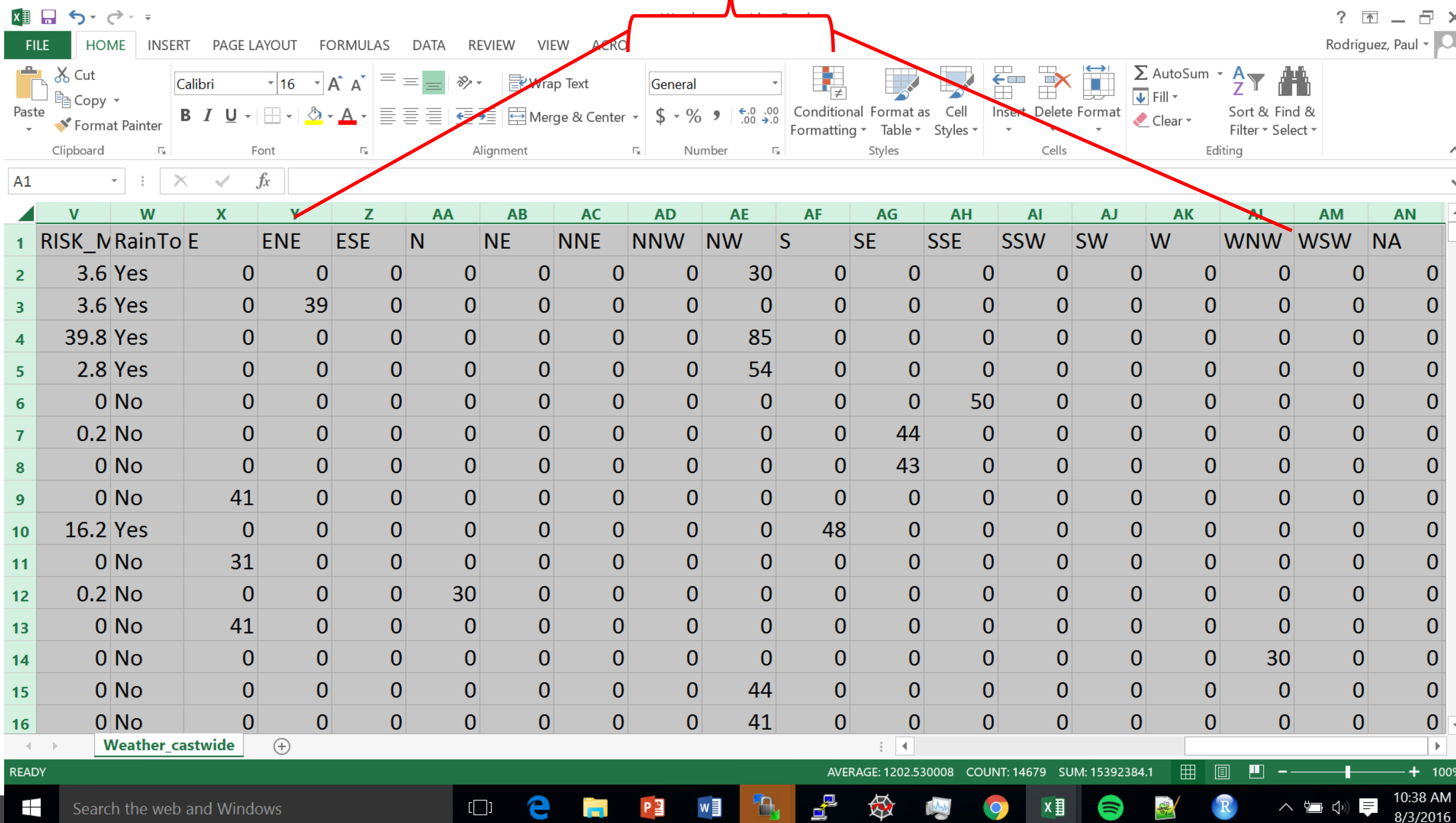
```
install.packages('reshape2')
library(reshape2)
W_wide   =dcast(W_df,
          formula=Date+Location+ ...~ WindGustDir,
          fill=0,
           value.var="WindGustSpeed")
```

this could be 0 or NA

indicate variable that has the repeated measurement values

Transformed Data Matrix

Now: WindGustDir values each have their own column



	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN
1	RISK_M	RainTo	E	ENE	ESE	N	NE	NNE	NNW	NW	S	SE	SSE	SSW	SW	W	WNW	WSW	NA
2	3.6	Yes	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0
3	3.6	Yes	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	39.8	Yes	0	0	0	0	0	0	0	85	0	0	0	0	0	0	0	0	0
5	2.8	Yes	0	0	0	0	0	0	0	54	0	0	0	0	0	0	0	0	0
6	0	No	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0
7	0.2	No	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0
8	0	No	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0
9	0	No	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	16.2	Yes	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0
11	0	No	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0.2	No	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	No	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	No	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0
15	0	No	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0
16	0	No	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0

Extra to try:

```
# wide to long: ie 'melt' repeated measure into long
#          table
W_melt   =melt(W_cast,
        na.rm=TRUE,
        measure.vars=c(23:39),
        variable.name="WindGustDir_cast")
```

The repeated measures are now in columns 23 to 30

pause

Reading Material

- **Data Preparation for Data Mining by Dorian Pyle**
  - http://www.ebook3000.com/Data-Preparation-for-Data-Mining_88909.html
- **Data mining – Practical Machine learning tools and techniques by Witten & Frank**
  - http://books.google.com

Many Variables

- **More variables => more information, but also more noise and more ways of interactions**

- **2 ways to handle many variables**
  - Variable Selection
  - Dimension reduction methods

Variable selection vs Dimensionality Reduction

- **Prior to algorithm, depends on data**
  - For large P, with noise particular to variables, try variable selection
  - For large P, diffuse noise, try dimension reduction by Matrix Factorization

Variable selection

- **Heuristic methods:**

  remove variables with low correlations to outcome

  (other criteria: information gain, sensitivity, etc…)

- **Step wise: add 1 variable at a time and test algorithm on samples**

Variable selection

- **Some algorithms are robust to extra noise variables**

- E.g. Least Angle Regression (L_1 penalty),

penalize small effect sizes (zero them out)

- E.g. Random Forest outputs 'importance'

low importance implies small error effect in the model when removed or permuted

Matrix Factorization:

Given a numeric matrix, can we reduce the number of columns?

conversely

Can we find interesting subspaces?

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- Yes, if features are constant or redundant

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Matrix Factorization:

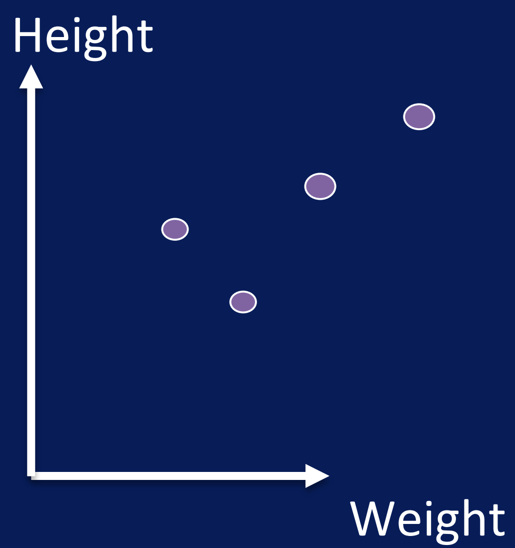
Given a numeric matrix, can we reduce the number of columns?

- Yes, if features are constant or redundant
- Yes, if features only contribute noise (conversely, want features that contribute to variations of the data)

Example: 2D data

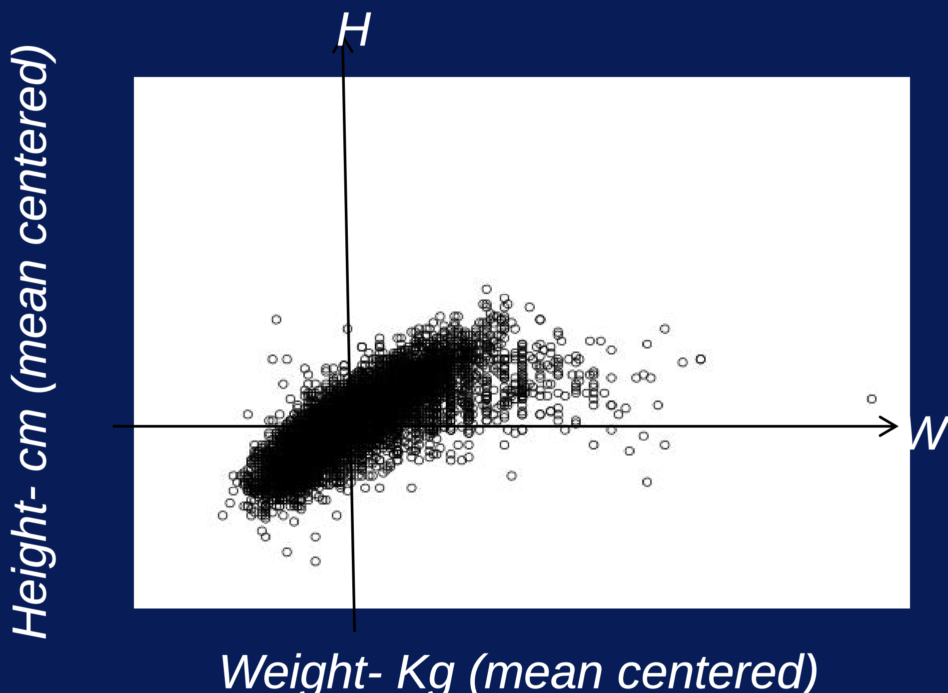
	Weight	Height
S1	50	179
S2	66	175
S3	74	180
S4	94	192

PLOT



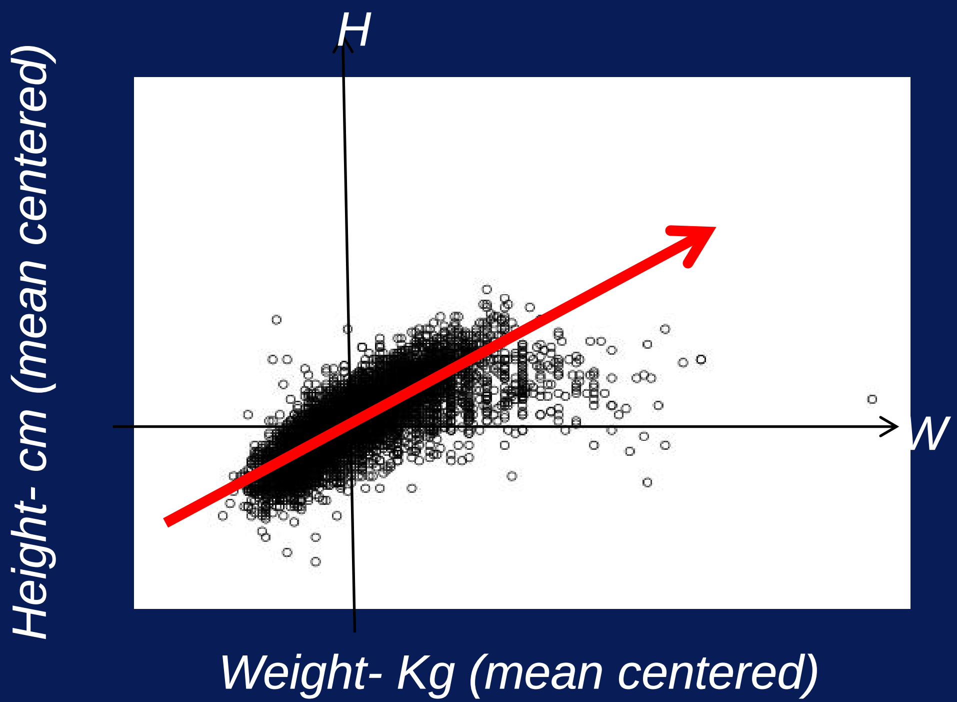
this is the input space

Example: Athletes’ Height by Weight



Find a line that aligns with the data.

Example: Athletes' Height by Weight



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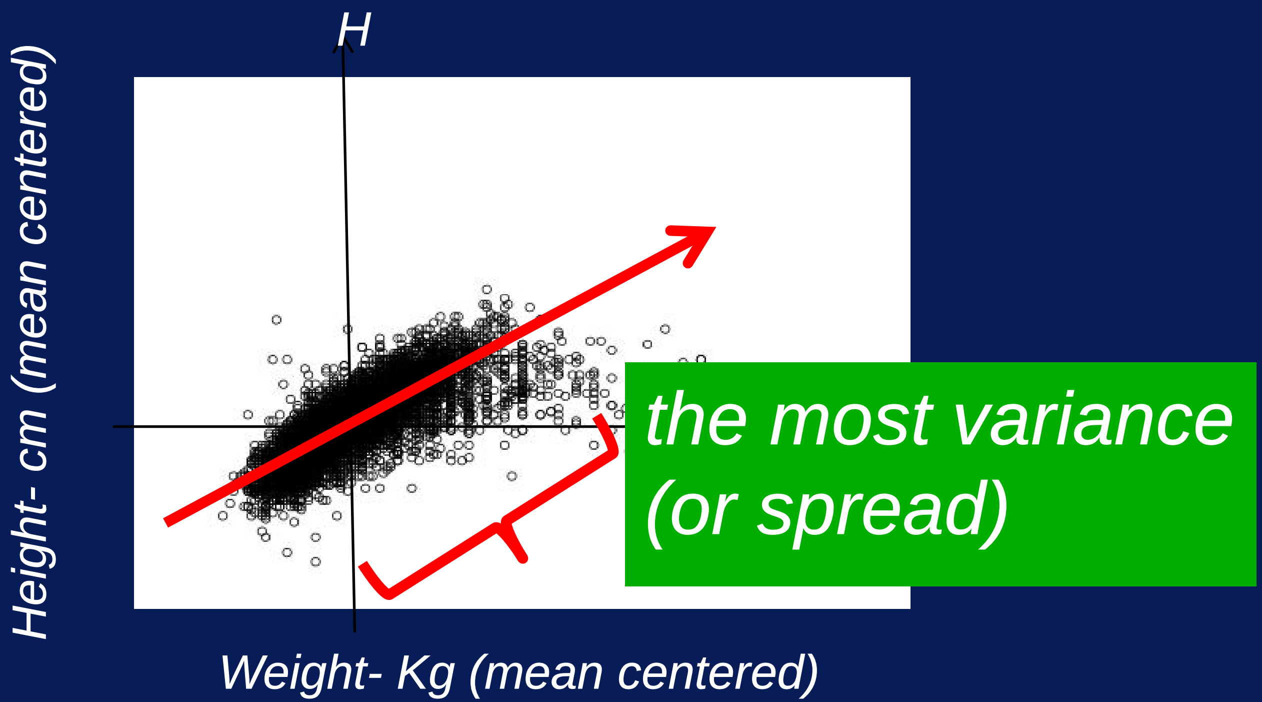

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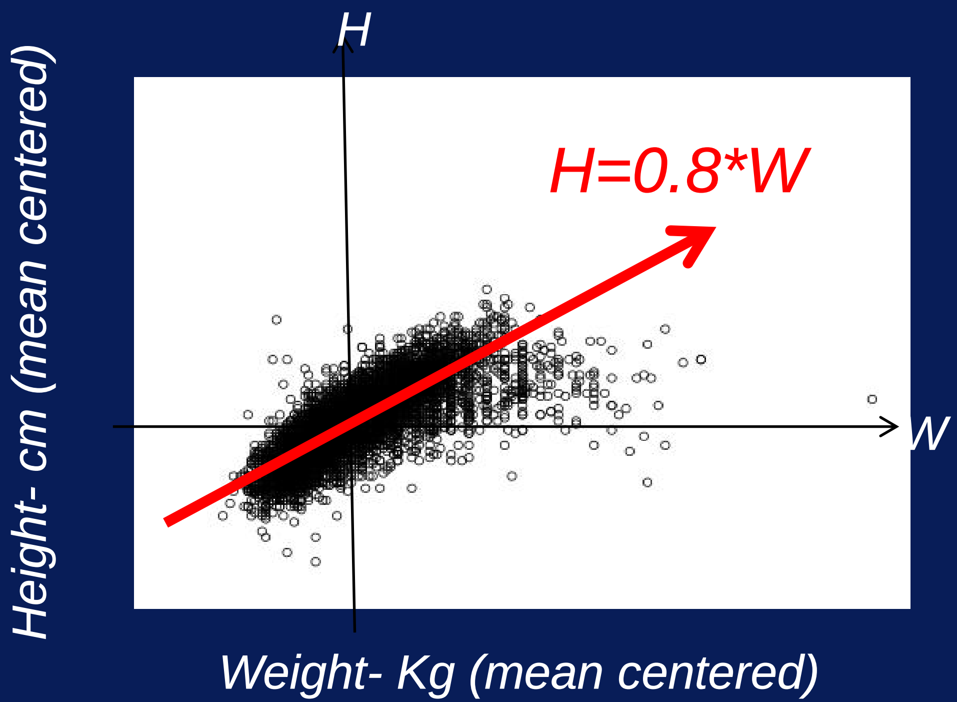
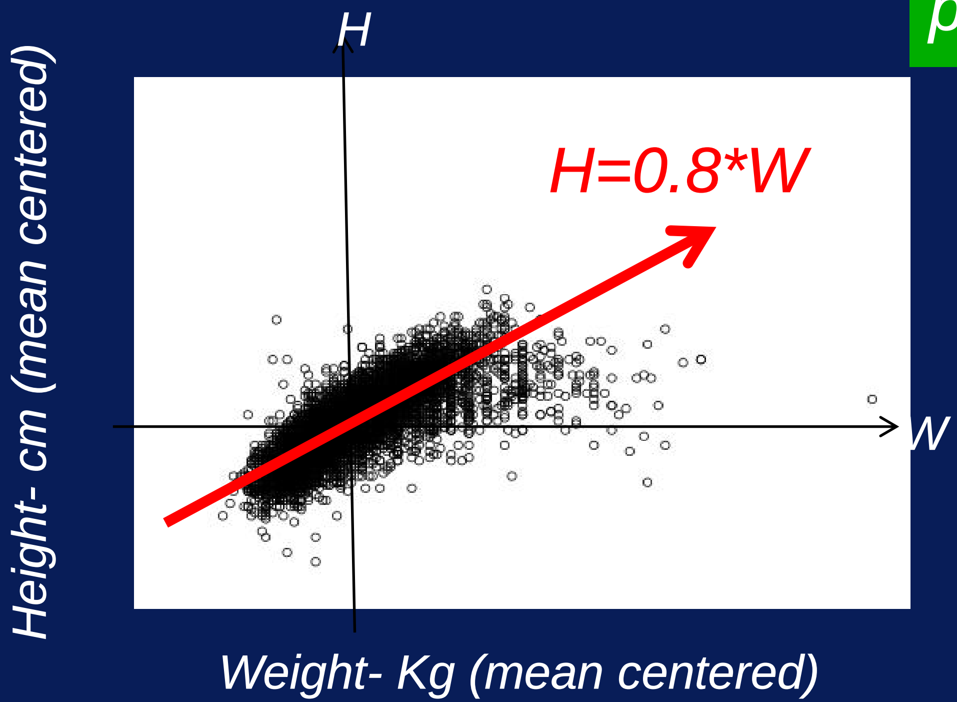


Find a line that aligns with the data.

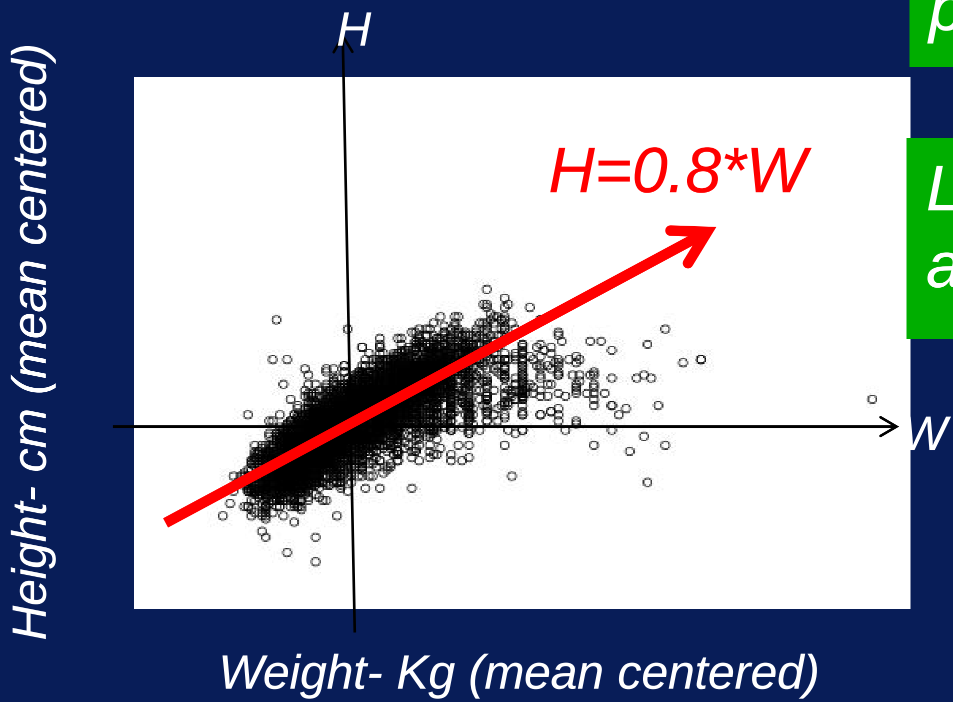
Note that W=1,H=0.8 is a point on the line, for example.



Find a line that aligns with the data.

Note that W=1,H=0.8 is a point on the line, for example.

Let [1 0.8] represent the line, as a combination of W & H.



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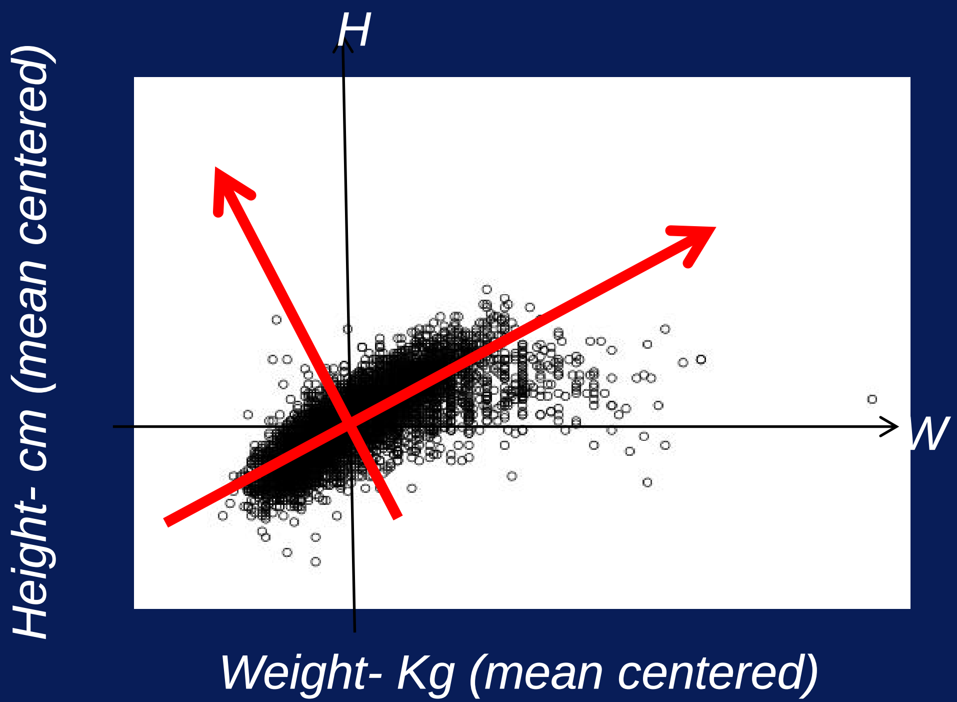
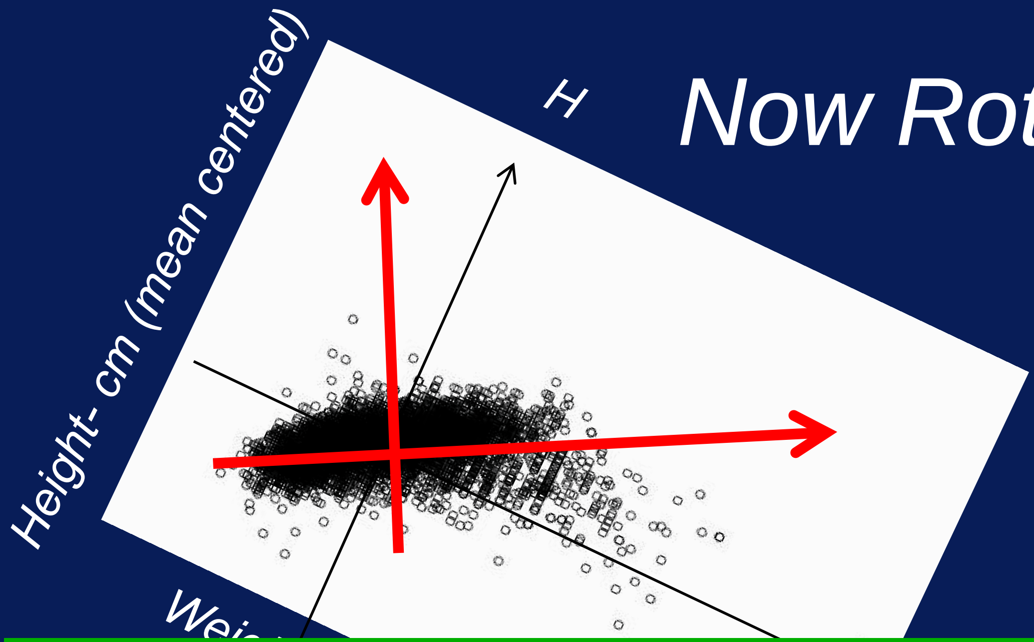


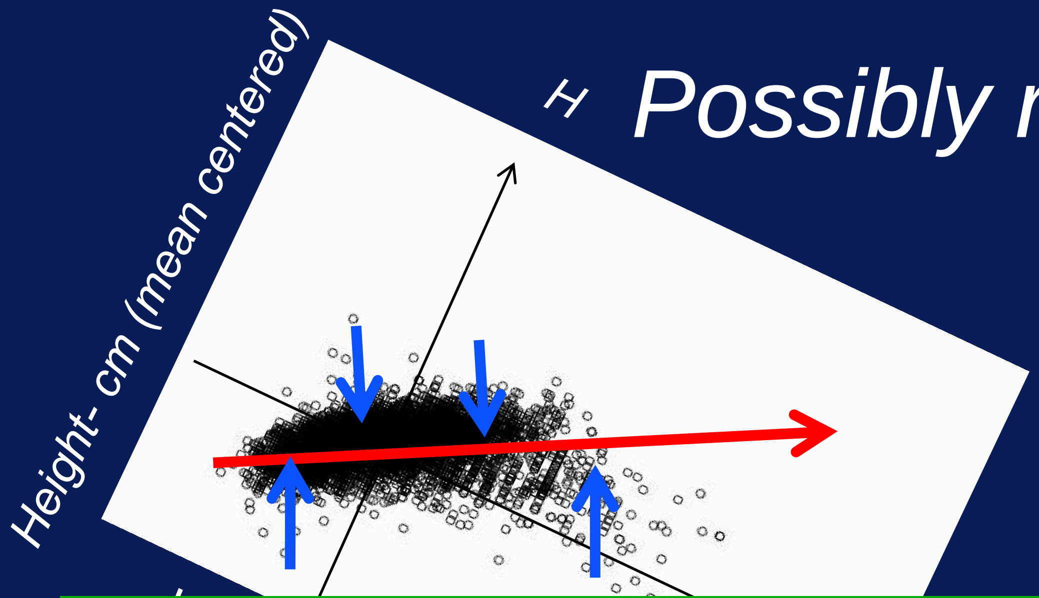
The next direction of most variance.

Now Rotate Axis



New axis (AKA features) defined as combinations of old features

Possibly reduce dimensions

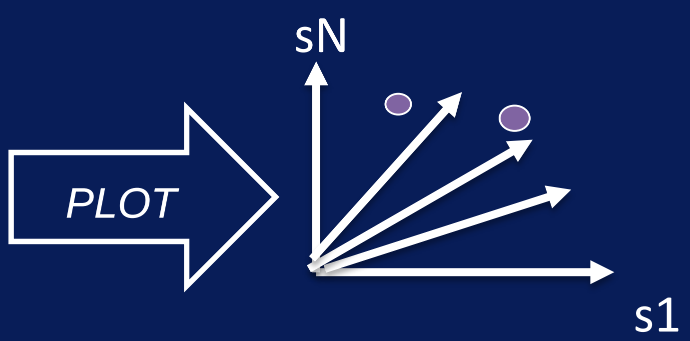


Project all points to one axis

(defined by the [1 0.8] 2D vector)

2D data transposed to 2 points in high dimensional space

	s1	s2	s3	…
Height	179	175	180	…
Weight	50	66	74	…



2D data transposed to 2 points in high dimensional space

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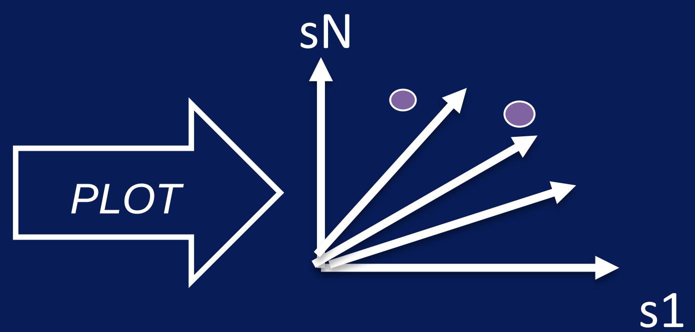

Same process as before, but now factors are N-dimensional vectors

- Best Known Factorization Algorithms:
  - SVD (singular value decomposition)
  - PCA (principle component analysis)

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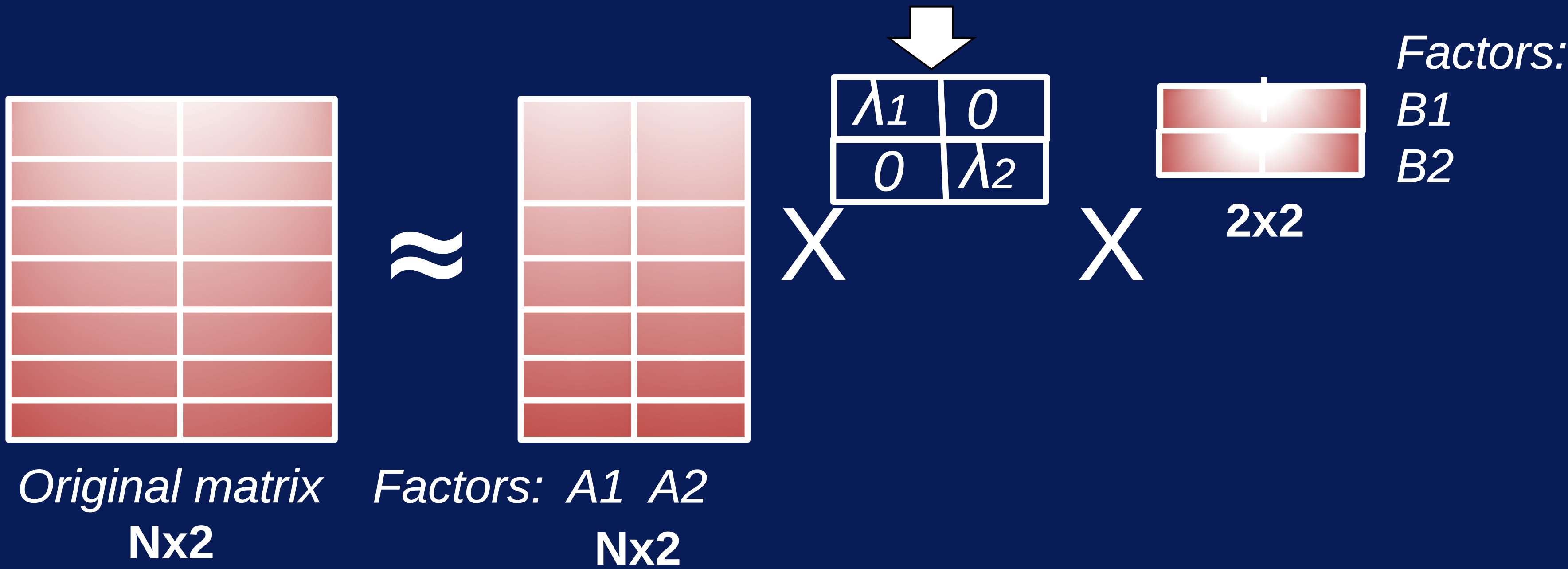
    SVD (singular value decomposition)

    PCA (principle component analysis)

SVD more generally works on non square matrices

SVD: factors and 'singular' scale values



- More generally:

Factorization Algorithms may vary depending on criterion for how factors ‘align’ with data.

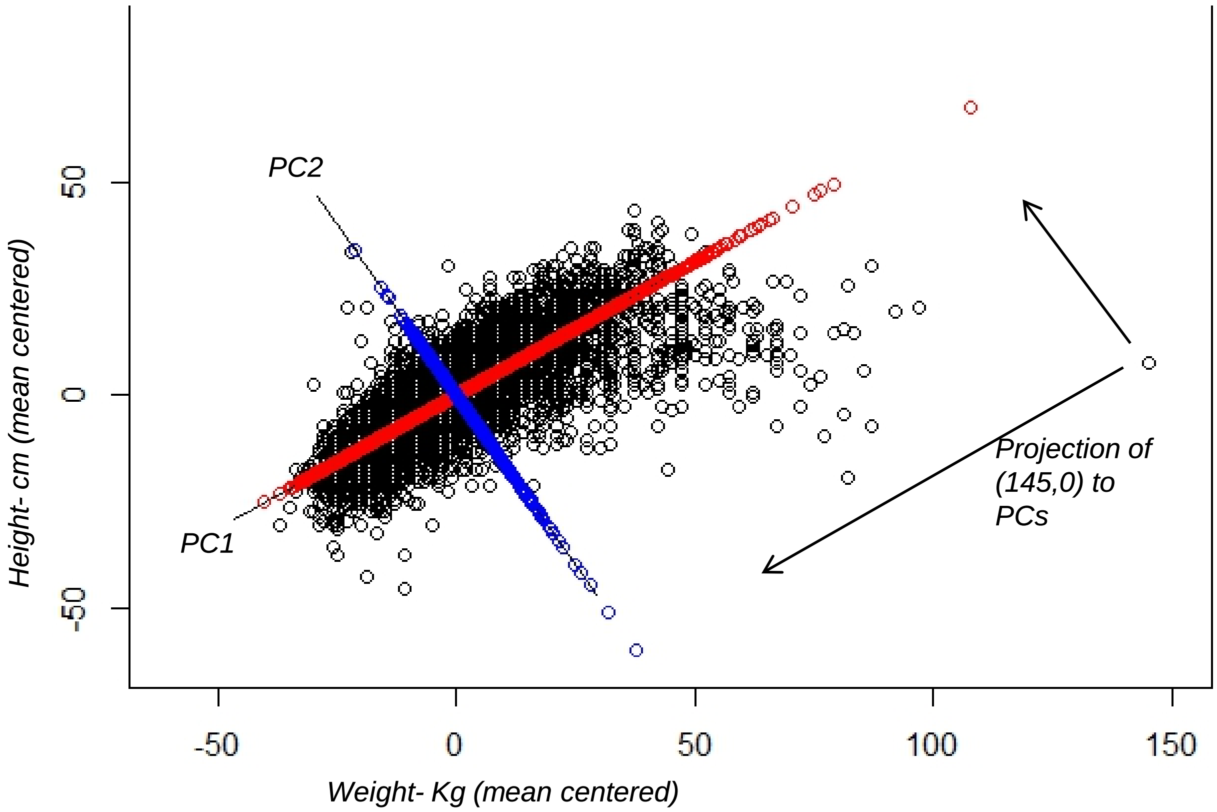
- More generally:

Factorization Algorithms may vary depending on criterion for how factors ‘align’ with data.

- Number of factors to use depends on tradeoff of good approximation vs good dimensional reduction

Can use cross validation or heuristics to choose.

Note: PCA conserves and reorders variance



Total Variance Conserved:

Var in Weight

+

Var in Height

=

Var in PC1 +

Var in PC2

In general:

Var in PC1>

Var in PC2>

Var in PC3…

Summary: Principle Components

- **Can choose *k* heuristically as approximation improves, or choose *k* so that high percent (ie 80-95%) of data variance accounted for**
- **aka Singular Value Decomposition**

  PCA on square matrices only

  SVD gives same vectors on square matrices
- **Works for numeric data only**
- **For higher dimensional data, use factors to visualize 2 factors at a time**

SVD Exercise

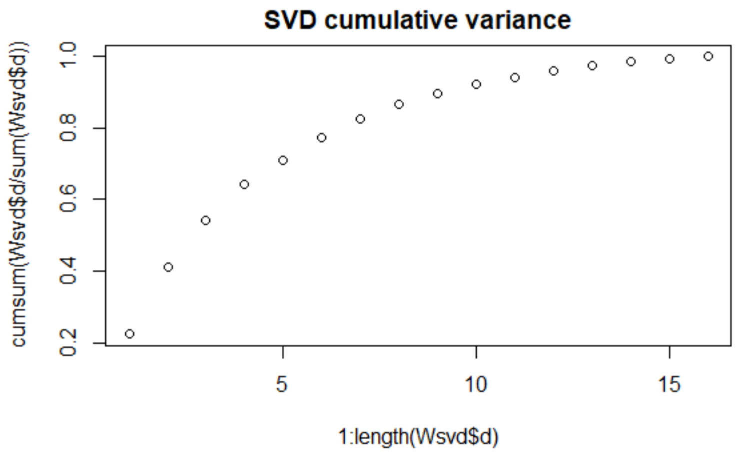
- Overview
  - Run on numeric fields of weather data
  - Run SVD and select smaller number of dimensions
  - Run linear model with original and reduced data

Later, we'll compare SVD components with Clustering

```
#W_num is only numeric or integer fields of Weather data
> Wsvd=svd(W_num)

> str(Wsvd)
List of 3
 $ d: num [1:9] 27442.7 231.2 96.4 68.2 44.5 ...
 $ u: num [1:363, 1:9] -0.0524 -0.0521 -0.052 -0.0519 -0.0525 ...
 $ v: num [1:9, 1:9] -0.005042 -0.014276 -0.000969 -0.00314 -0.005491 ...
```

Exercise highlights



Compare Linear Model results, using Y = raintomorrow:

look for residual standard error values and degree of freedom,

look at coefficient estimates

```
Call:
lm(formula = Ymc ~ W_mncntr)
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          -1.124e-15  1.641e-02   0.000 1.000000
W_mncntrMinTemp      -1.368e-02  1.013e-02  -1.350 0.177844
W_mncntrMaxTemp       1.035e-02  2.010e-02   0.515 0.607120
W_mncntrRainfall      4.269e-03  4.471e-03   0.955 0.340442
W_mncntrEvaporation   2.690e-02  1.010e-02   2.663 0.008137 **
W_mncntrSunshine     -3.446e-02  9.898e-03  -3.482 0.000570 ***
W_mncntrPressure9am   6.569e-02  1.325e-02   4.960 1.16e-06 ***
W_mncntrPressure3pm  -8.047e-02  1.337e-02  -6.021 4.89e-09 ***

Residual standard error: 0.2971 on 311 degrees of freedom

Call:
lm(formula = Ymc ~ W_dfred)
Coefficients: (13 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.874e-16  1.808e-02   0.000 1.000000
W_dfred1     4.519e+00  1.242e+00   3.638 0.000320 ***
W_dfred2     4.650e+00  1.307e+00   3.559 0.000429 ***
W_dfred3     1.580e+00  4.357e-01   3.627 0.000333 ***
W_dfred4            NA         NA      NA       NA
W_dfred5            NA         NA      NA       NA

Residual standard error: 0.3274 on 324 degrees of freedom
```

- **end**