Presenting computational results

E6891 Lecture 11
2014-04-09

Today's plan

- Communicating numerical information
  - text (tables)
  - visuals (plots, images)
  - statistical summaries

- Much borrowing from
  - Andrew Gelman, Cristian Pasarica & Rahul Dodhia (2002) Let's Practice What We Preach, The American Statistician, 56:2, 121-130

Why a lecture about presentation?

- Step 1 of reproducing a result:
  - what *is* the result?
- Reproducibility depends on clarity
- Clarity can be difficult!

Aside

- I'll use examples mainly from my own work
- These will ***not*** be perfect!
  - I'm not an info-vis expert
- Let's beat up on them together!

Communicating numerical data

- Quantitative information
- Qualitative comparisons
- Trends in data
- Statistical quantities

How should I present *X*?

- What should the reader take away?
  - Raw information? (**Quantitative**)
  - Comparisons? Trends? (**Qualitative**)

- Always put yourself in place of the reader

- Figures should support the text
  - not vice versa!

Tables

- Best for reporting **small amounts** of data with **high precision**
- Useful when data has intrinsic value
  - e.g., sample size, parameter range
- Not great for comparisons or large data
  - Trends can be obscure
  - Not space-efficient

Table example (not so great)

Data Set/Items	Songs	Albums	Artists	Users	Ratings/Evts.
Yahoo! Music	624,961 in total			1,000,990	262,810,175
MSD	1,000,000			1,019,318	48,373,586
Last.fm – 360K			186,642	359,347	
Last.fm – 1K			107,528	992	
MusicMicro	71,410		19,529	136,866	594,306
MMTD	133,968		25,060	215,375	1,086,808
AotM-2011	98,359			16,204	859,449

Table 1 Statistics of public data sets for music recommendation research.

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Good

- Vertical arrangement
- Easy to interpret data

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Table 1 Statistics of public data sets for music recommendation research.

Good

- Vertical arrangement
- Easy to interpret data

Bad

- Line clutter
- Excessive detail
- Center-alignment
- Unused column
- A lot of border lines

Table example (improved)

Collection		Songs	Artists	Items	Users	Events
Yahoo! Music	[1]	—	—	625K	1M	263M
MSD	[2]	1M	—	—	1M	48M
Last.fm – 360K	[3]	—	187K	187K	356K	—
Last.fm – 1K	[3]	—	107K	107K	1K	—
MusicMicro	[4]	71K	20K	71K	137K	594K
MMTD	[5]	134K	25K	159K	215K	1M
AotM-2011	[6]	98K	—	98K	16K	859K

Table 1: Statistics of public data sets for music recommendation research.

Improvements

- Removed clutter
- Simplified headers
- Explicit missing values
- In-place citations

Still bad

- “Items” may be confusing
  - but that’s the data…
  - clarify in text!

Best practices: tables

- **Do** use when numbers have intrinsic value
- **Do** arrange by column, not row
- **Do not** clutter with lines/rules/borders
- **Do not** use *excessive* precision
- **Do not** overload

Graphics can serve many purposes

- Space-efficient communication
- Highlight trends in data
- Help the reader form comparisons

Graphics can’t...

- … make your point for you
  - *But they can help*
- … tell the complete story
  - Choosing what to leave out is important!
- … make themselves presentable
  - No, not even with the Matlab defaults!

How should I display my data?

- What's the data?
  - Continuous
  - Ordered? Sequential?
  - Categorical? Binary?
  - Bounded? Non-negative? [0, 1]?
- What's the comparison?
  - Absolute (e.g., classifier accuracy)
  - Relative (e.g., histogram data)
  - Something else entirely?

No one-size-fits-all solution...

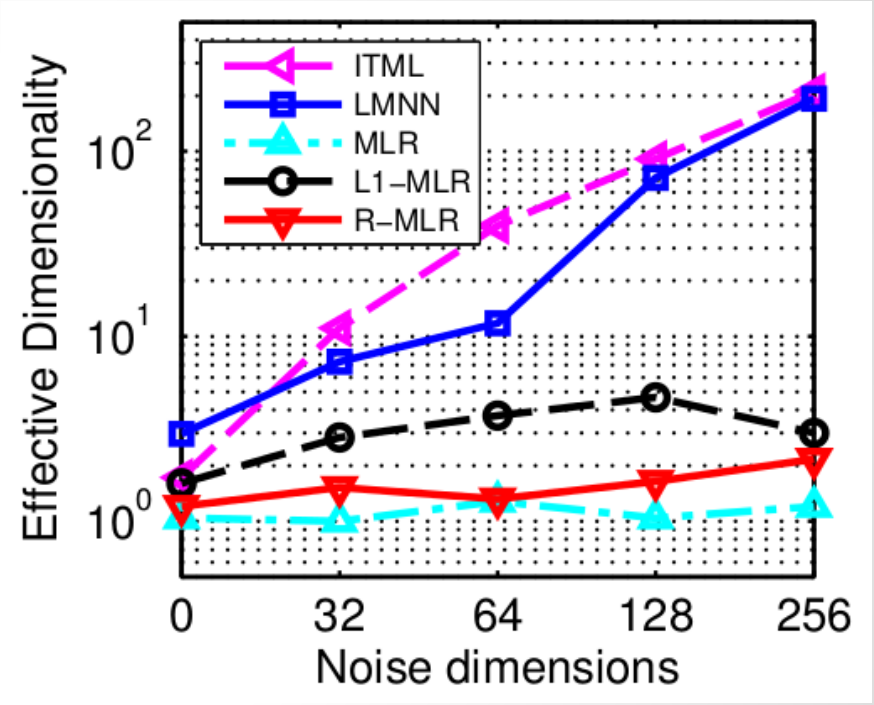
- But you can get really far with:
  - **line** (grouped data)
  - **scatter** (ungrouped data)

- Primary goal: **simplicity**

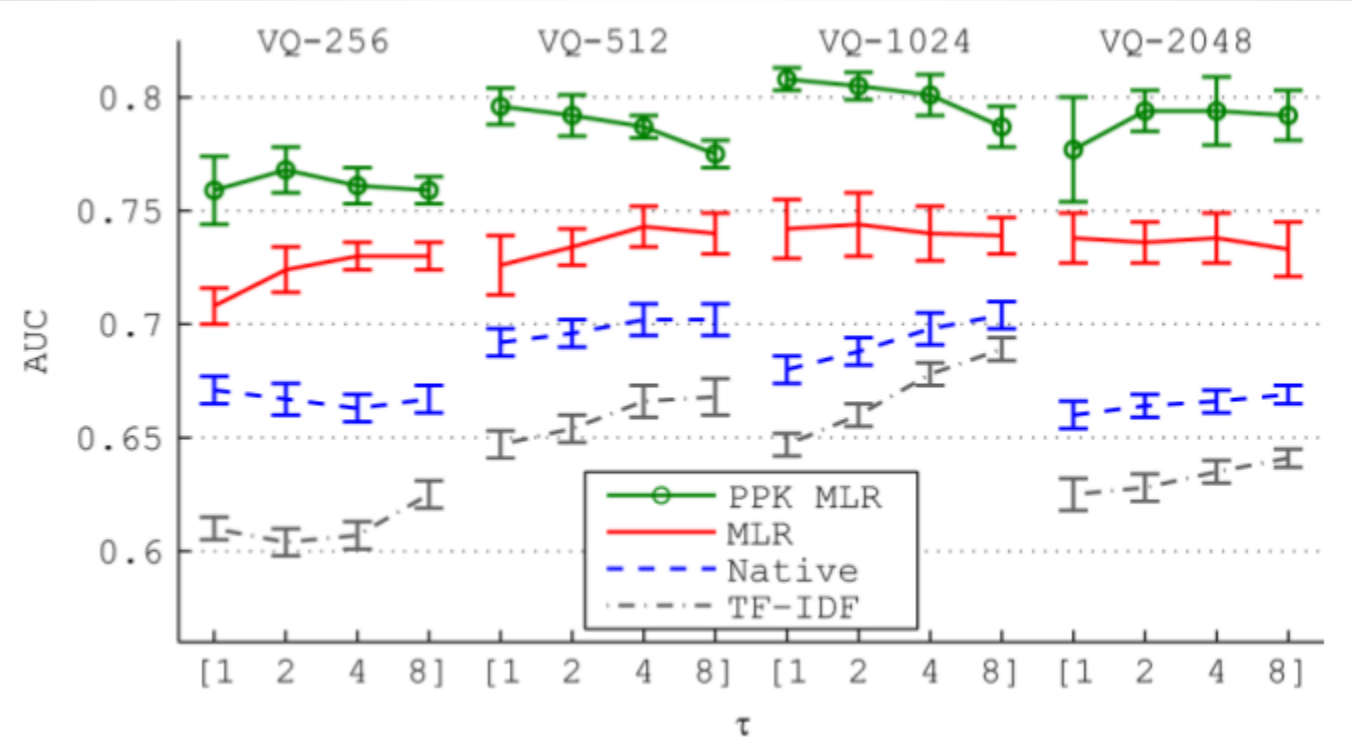
- Prefer many simple plots to one complex plot

Lines

- Line grouping helps illustrate trends
- Quantity to be compared is on the vertical axis



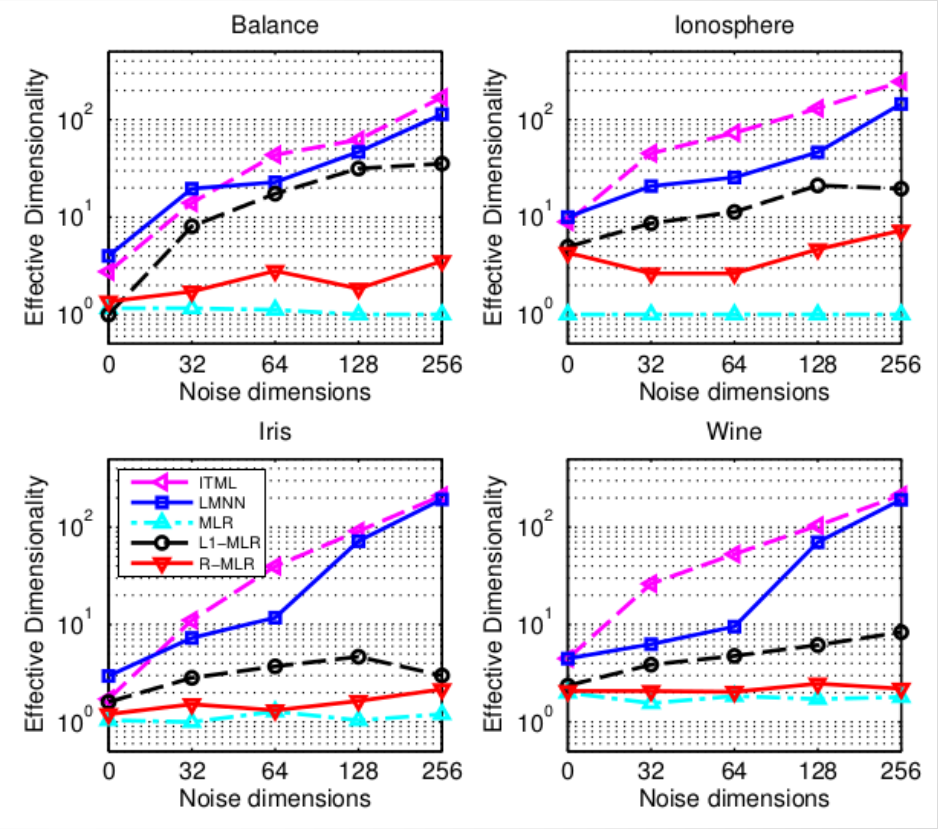
Information overload



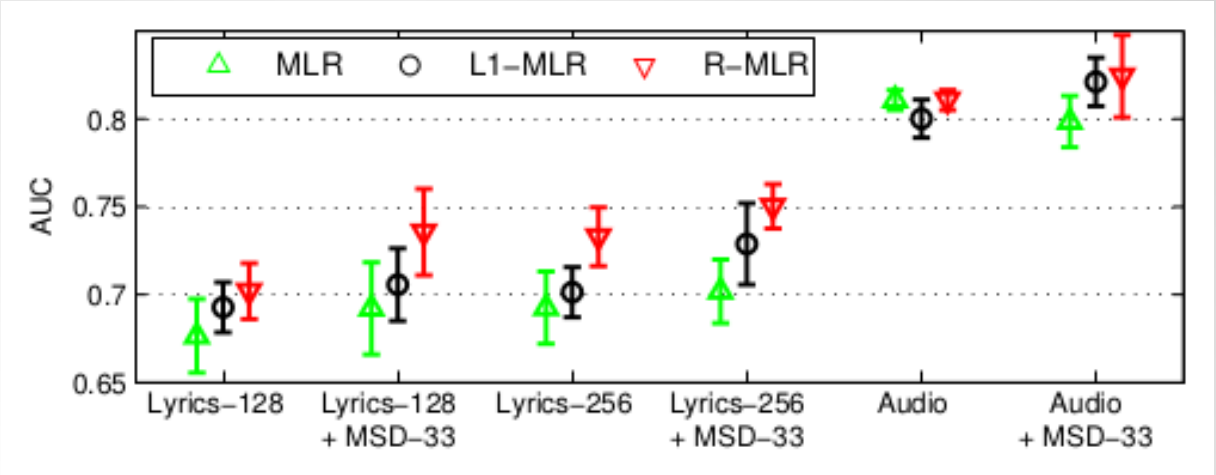
- Too many comparisons for one figure:
  - (4 methods) * (4 VQ values) * (4 t values)

Multiple plots

- Some redundancy is okay
- Restrict intended comparisons to lie within one subplot
- Minimize inter-plot comparisons

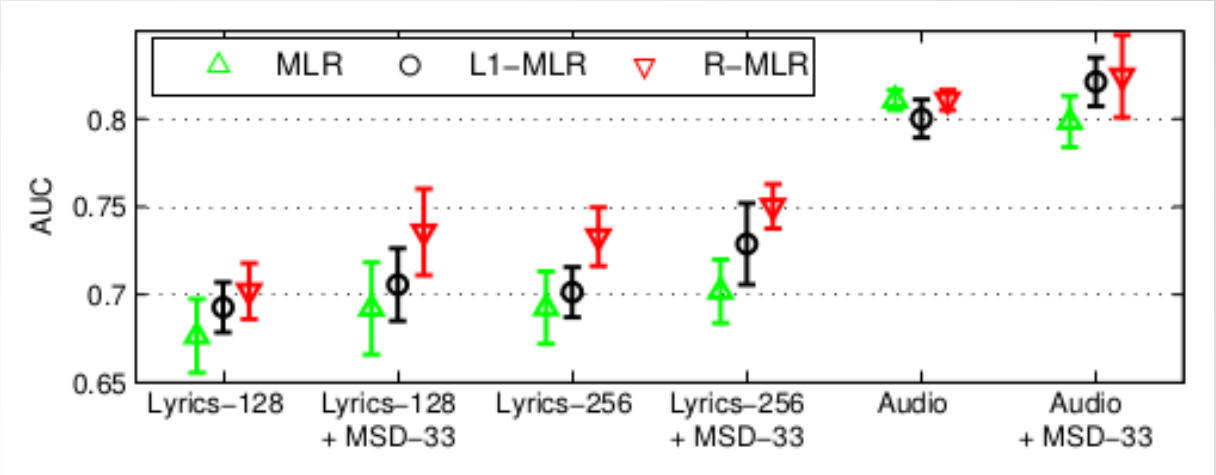


Scatter



- Why not **lines**?
  - no meaningful ordering
  - clutter

Scatter



- Why not **lines**?
  - no meaningful ordering
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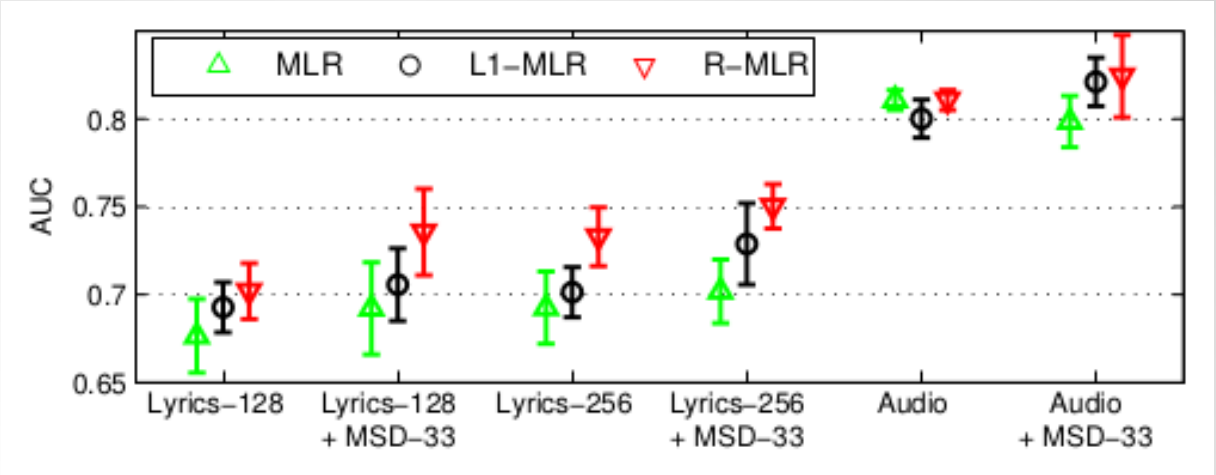
- Why not **bars**?
  - obscures error bars
  - invisible baseline
  - fractional comparisons aren’t relevant

Scatter



- Why not **lines**?
  - no meaningful ordering
  - clutter
- Why not **bars**?
  - obscures error bars
  - invisible baseline
  - fractional comparisons aren't relevant

Bad

- [0.65, 0.85]?
- Maybe overloaded
- Bright green can be hard to see

Best practices: plots / subplots

- Label all axes
- Quantity of comparison on the y-axis
- Use meaningful limits when possible
  - Be consistent when multi-plotting
- Be consistent with markers/styles
- Don’t rely too much on color

(..continued)

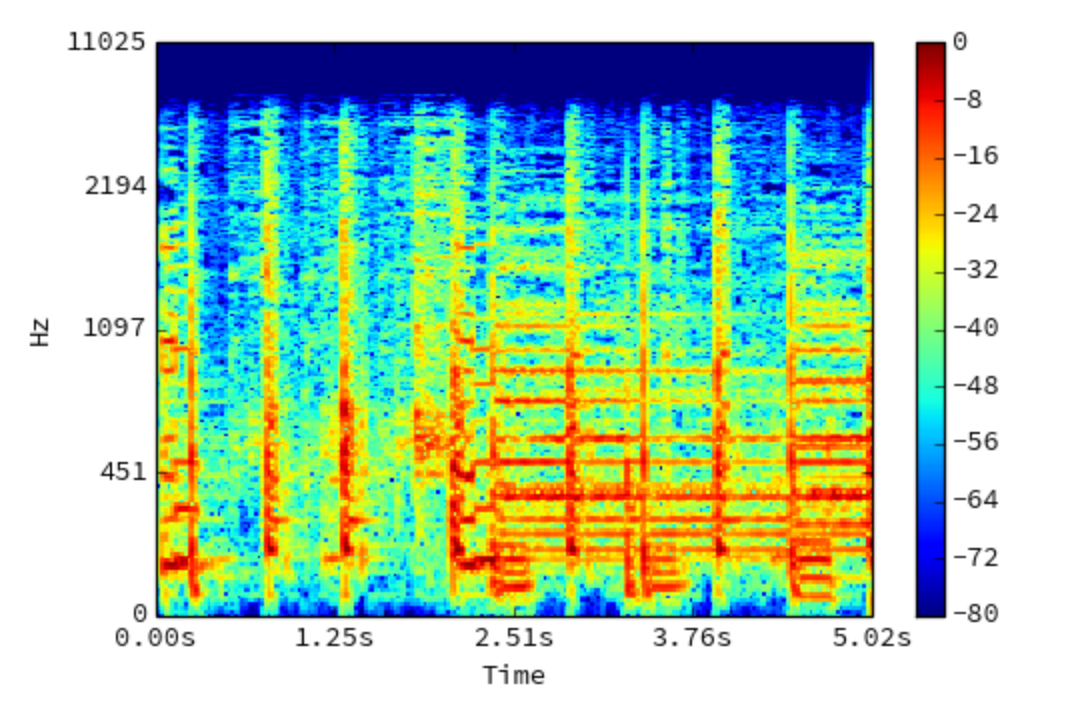
- If using a legend, match the ordering to the visualization
- Better yet, label points/curves directly
  - As long as it’s still readable...
- Use captions to resolve ambiguities
- Empty space can be ok, if it’s meaningful

About color...

- Color is the easiest thing to get wrong

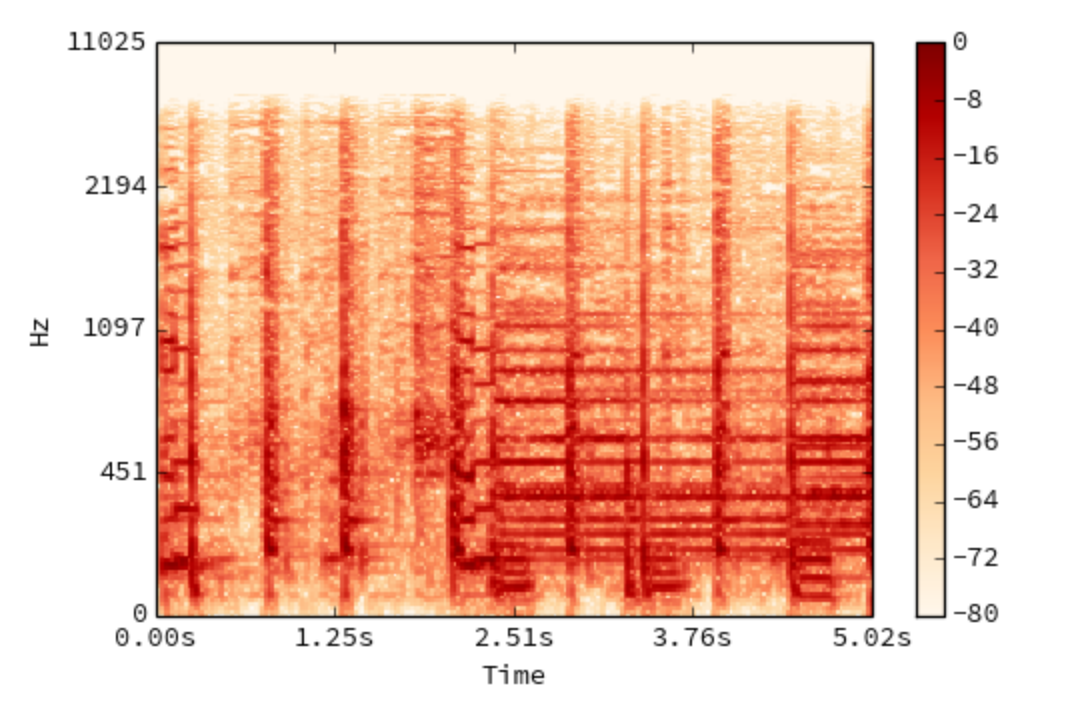
- Things to watch out for:
  - printer-friendly
  - projector-friendly
  - colorblind-friendly
  - unintended (dis)similarity

Example: spectrogram



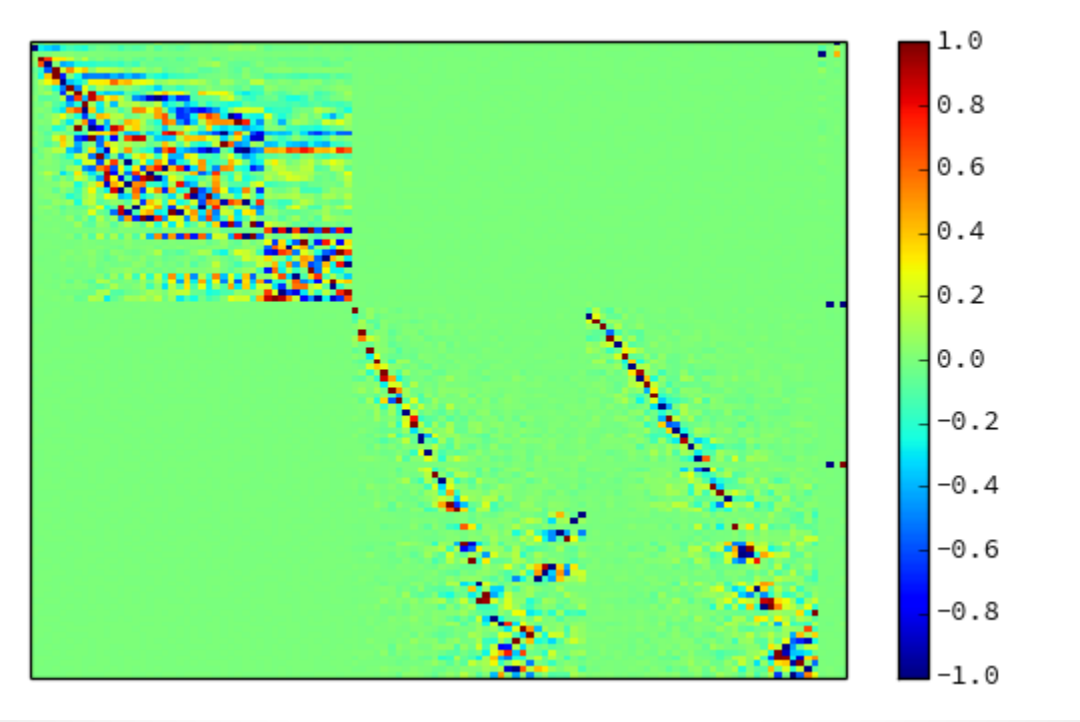
- *Jet* colormap provides **false contrast**
- Does not translate to grayscale

Example: spectrogram

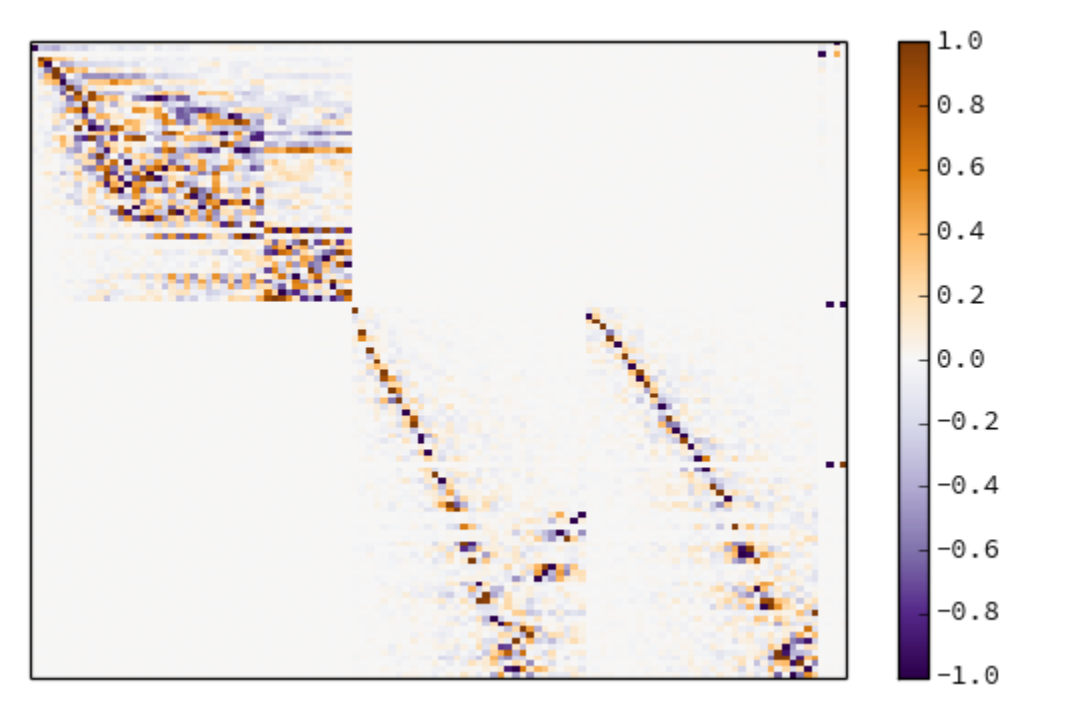


- But the data is bounded: (-∞, 0]
- Use a sequential gradient
- Observe conventions as far as possible

Example: signed data



Example: signed data



- **Divergent** colormaps visualize both *magnitude* and *direction* (sign)

What makes color difficult?

- Numerical data -> ~~RGB~~ **HSV**
- Input data can be multi-dimensional
  - **Sequential** data is 1d (distance from boundary)
  - **Divergent** data is 2d (magnitude, direction)
- Color parameters are non-linear
  - … so is human perception
- **Physical** and **perceptual** constraints

Choosing a colormap 1

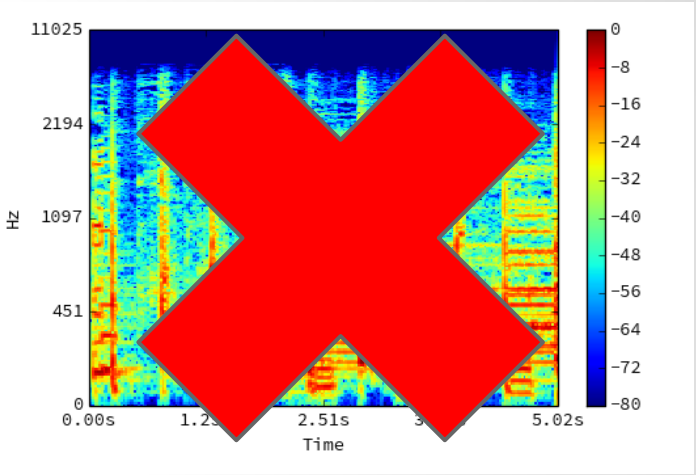
Color Brewer

Choosing a colormap 2

Color-blind simulator

Best practices: colormaps

- Sequential
  - **OrRd**
  - **Greys**
  - (or any single-hue gradient)
- Divergent
  - **PuOr**



- Never use **jet**
  - Rainbow maps can be ok for categorical data...
  - … but continuous rainbow maps are dangerous

Statistical quantities

- Results are typically statistical, e.g.:
  - classifier accuracy on a test sample
  - P[sample data | model]
- We use finite-sample approximations to estimate unobservable quantities
  - e.g., true accuracy of the classifier
- Approximations imply **uncertainty**
  - this should be reported too!

Error bars

- Repeating an experiment with random sampling helps us to quantity uncertainty
  - leave-one-out, k-fold cross-validation, etc.

- Depending on the statistic being reported, different notions of uncertainty make sense
  - standard deviation
  - quantiles/inter-quartile range

Hypothesis testing

- Somewhat dicey territory these days…
- Quantify confidence in a statistical claim
  - e.g., difference in accuracy between two classifiers
  - are they *actually* different?
- Does the data support my hypothesis?
  - Assume the contrary: *the null hypothesis*
  - Use data to refute the null hypothesis

p-values

The p-value is the probability (under [the null hypothesis]) of observing a value of the test statistic the same as or more extreme than what was actually observed.

Wasserman, L. *All of statistics: a concise course in statistical inference*. Springer, 2004.

- **NOT** P[null hypothesis | data]

- A p-value can be high if
  - the null hypothesis is true (*and it almost never is!*)
  - the test statistic has low power

Pitfalls of p-values

- Rejection threshold is arbitrary
  - 0.05 vs 0.051?
  - It's better to report values directly than claim significance against a fixed threshold
- p-value **does not** measure effect size
  - with enough samples, any difference is "significant"
  - but is it **meaningful**?
- We usually already know the null hypothesis is false

Discussion