0.1 General Structure

```
  rating_density = alt.Chart(df, title="Title").encode(
    x=alt.X('col1:Q',title='the value',scale=alt.Scale(domain=[0,
          10000]),axis=alt.Axis(format='~s',grid=False,tickCount=10)),
    y=alt.Y('density:Q',title='density',scale=alt.Scale(domain=[0,
          0.000100]),axis=alt.Axis(format='.6f',grid=False)).stack(False),
    color=alt.Color('where:N', scale=alt.Scale(domain=['My state',
          'Neighboring states'],range=['#A0D2E8', '#A0E8AF']),
        legend=alt.Legend(orient='top'))
).properties( width=600, height=400)
```

```
options(repr.plot.width=7, repr.plot.height=3)
chart <- ggplot(wages) + aes(x = salary,y = when,fill = when) +
    geom_violin() + geom_point(stat = 'summary', fun = median,
          color = 'White') +
    geom_point(stat = 'summary', fun = mean, color = 'Black') +
    labs(x = "Worker Salary ($)",y = "When",title = "Title") +
    scale_x_continuous(limits = c(10, 40), oob =
          scales::oob_keep,labels = scales::dollar_format())
```

0.2 Heat Maps

A 2D histogram is a type of heatmap, where count is mapped to color, you could also have used a mark that maps size to color, which might even be more effective but that is not as commonly seen.

```
alt.Chart(df).mark_rect().encode(alt.X('col1').bin(maxbins=40),
alt.Y('col2').bin(maxbins=40),alt.Color('count()'))
```

Instead of squares,**hexagonal bins** can be used. These have theoretically superior qualities over squares, such as a more natural notation of neighbors.
2 dimensional **KDEs** in ggplot. This works just like 1D KDEs, except that the kernel on each data point extends in 2 dimensions
Use **ridges contours**, similar to a topographic map. These contour plots are often less intuitive than the density plot above, so the recommendation is to use the density plot instead.

```
ggplot(df) + aes(x = col1, y = col2) + geom_bin2d() or geom_hex()
      or geom_density_2d_filled() or geom_density_2d()
```

0.3 Axis Label Formatting

Scientific Notation & Grid Tick Modifications Scientific notation, Consider formatting axis labels using plain numbers or appropriate unit prefixes (e.g., thousands, millions, micro, milli) to improve readability.

```
.alt.X('col').axis(format='e') # For e like notation
.alt.X('col').axis(format='s') # Standard international (SI) units
.alt.X('col').axis(format='~s') # Removes trailing zeros
.alt.X('col').axis(format='\$~s') # Formaters can also be combined.
.alt.X('col').axis(format='.1%') # Decimal formats
.alt.X('col').axis(None) #Remove an axis altogether
.alt.Y('col').axis(tickCount=2) #ticks on axis
.alt.Y('col').axis(grid=False) #Remove grid
.alt.Y('col').sort('-y') #Sort y axis
alt.Y('coly').bin(maxbins=400).scale(domain=[0, 2000]), #Set scale
alt.themes.enable('dark') #Dark theme scale
alt.Color('count()').legend(None) # remove a legend
alt.Y('coly').bin(maxbins=400).scale(domain=(0, 2000),
      reverse=True), #Reversing an axis
alt.Y('col:Q',bin=alt.Bin(maxbins=20),
        title='Y Label', #Set Label
        axis=alt.Axis(format='.1%', titleFontSize=14,
              labelFontSize=12))
```

```
ggplot(df) + aes(x = colx,y = coly) + geom_hex() +
  guides(fill = "none") + # remove a legend
  scale_x_continuous(
    labels = scales::label_dollar(scale = .001, suffix = "K"),
    labels = scales::label_number(scale_cut = scales::cut_si('')),
    limits = c(10, 31), oob = scales::oob_keep, #scale limit
    limits = c(2000, 0), trans = 'reverse', #reversing an axis
    labels = scales::label_dollar(), #label formater
    breaks = scales::pretty_breaks(n = 10) #tick count
  )
```

0.4 Trendlines

Mean Line also called "lines of best fit", or "fitted lines" are good to highlight general trends in the data that can be hard to elucidate by looking at the raw data points.

```
points + points.mark_line().encode(y='mean(Horsepower)')
```

```
ggplot(cars) + aes(x = Year, y = Horsepower, color = Origin) +
  geom_point() + geom_line(stat = 'summary', fun = 'mean')
```

Regression Lines Easy-to-interpret trend line, use a rolling mean. It naturally highlights patterns as we would notice them visually and requires fewer statistical assumptions than methods like **linear regression**. regression line that is quadratic, polynomial

```
points + points.mark_line(size=3).transform_regression(
'Year','Horsepower',groupby=['Origin'],method='poly')
```

loess/lowess Lines Where the w stands for "weighted". You can fit multiple equations (usually linear and quadratic) to smaller subsets of the data, and add them together to get the final line. **bandwidth** parameter controls how much the loess fit should be influenced by local variation in the data, similar to the effect of the bandwidth parameter for a KDE. bandwidth of 1 corresponds to using all the data and will be similar to a linear regression

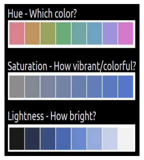
```
points + points.mark_line(size=3).transform_loess(
'Year','Horsepower',groupby=['Origin'],method='poly',bandwidth=0.8)
```

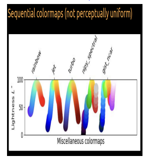
```
ggplot(cars) + #color the confidence interval the same as the lines.
aes(x = Year,y = Horsepower, color = Origin, fill = Origin) +
    geom_point() + geom_smooth() #Introduce CI
    geom_smooth(se = FALSE, linewidth = 1, span=1) #Introduce
          bandwidth use span
    geom_smooth(se = FALSE, linewidth = 1, method = 'lm') #linear
          regression instead of loess
```

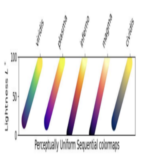
0.5 When to choose which trendline:

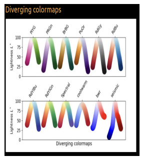
Rolling mean / mean: Best for clear, easy-to-read trends and general audiences. Simple and intuitive, but not suitable for predictions beyond your data. Linear (or similar model): Use when your data follows a clear equation. Good for showing consistent patterns and making predictions outside your data range. Loess (or smooth curve): Ideal for showing natural, flexible trends in current data without assuming a strict model, though poor for extrapolation.

0.6 Color schemes/maps:









Colormap is useful for (categorical, sequential, diverging, cyclic) and correlation maps
Categorical: Single color for each category
Sequential: Shades of a color

```
#Sequential
alt.Chart(iris).mark_circle(size=100).encode(x='col1', y='col2',
    color=alt.Color('petalWidth').scale(scheme='viridis',
          reverse=True))
#Diverging has a natural midpoint, correlation that is defined from
      -1 to 1
corr_df = data.gapminder().corr(
    numeric_only=True).stack().reset_index(name='corr')
alt.Chart(corr_df).mark_rect().encode(
    x='level_0',y='level_1',tooltip='corr',
    color=alt.Color('corr').scale(domain=(-1, 1),
    scheme='purpleorange'))
```

```
#Sequential
ggplot(iris) + aes(x = col1,y = col2,color = Petal.Width) +
    geom_point(size = 5) + scale_color_viridis_c()
#Diverging has a natural midpoint, correlation that is defined from
      -1 to 1
ggplot(corr_df) + aes(x = level_0,y = level_1,fill = corr) +
    geom_tile() + ggthemes::scale_fill_gradient2_tableau()
    + scale_color_manual(values = c('#FF7F50', '#4682B4',
          '#663399')) #Custom color mapping
```

0.7 Direct labeling instead of using a legend

```
lines = alt.Chart(stocks).mark_line().encode(
    x='date', y='price', color=alt.Color('symbol').legend(None))
text = alt.Chart(stock_order).mark_text(dx=20).encode(
    x='date', y='price', text='symbol', color='symbol')
lines + text
```

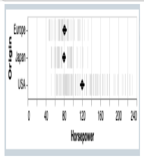
```
ggplot(stocks) +
    aes(x = date,y = price,color = symbol,label = symbol) +
    geom_line() + geom_text(data = stock_order, vjust=-1) +
    ggthemes::scale_color_tableau() + theme(legend.position =
          'none')
```

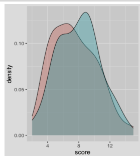
0.8 Confidence Intervals

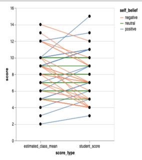
By default this mark show the standard deviation of the points, but we can change the extent to use bootstrapping on the sample data to construct the 95% confidence interval of the mean.

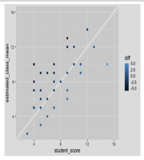
```
points.mark_errorband(extent='ci') +
      points.encode(y='mean(Horsepower)').mark_line()
err_bars = alt.Chart(cars).mark_errorbar(extent='ci',
      rule=alt.LineConfig(size=2)).encode(
    x='Horsepower',y='Origin')
(err_bars.mark_tick(color='lightgrey') + err_bars +
      err_bars.mark_point(color='black').encode(x='mean(Horsepower)'))
```

```
geom_line(stat = 'summary', fun = mean) + #for line chart with CI
geom_ribbon(stat = 'summary', fun.data = mean_cl_boot, alpha=0.5,
      color = NA)
geom_violin(color = NA, fill = 'steelblue', alpha = 0.4) + #for
      point chart with CI bar lines
geom_pointrange(stat = 'summary', fun.data = mean_cl_boot, size =
      0.7)
```









0.9 Pairwise comparisons

Slop plot above. A scatter plot could also work for this comparison, ideally with a diagonal line at zero difference. A good alternative to a pair-wise slope plot would be a scatter plot of the paired measurements or a histograms of the differences. This don't necessarily have all the advantages of a slope plot, but can often effectively visualize pair-wise measurements either on their own, or in combination with a slope plot.

```
ggplot(scores_this_year) + aes(x = score,fill = score_type) +
geom_density(alpha=0.4)
ggplot(plot) + aes(x=score_type,y=score,group=time) +
geom_line(aes(color = self_belief), size = 0.8) + geom_point(size=3)
p <- ggplot(scores_this_year |> pivot_wider(names_from =
      score_type, values_from = score)) +
    aes(x = student_score,
        y = estimated_class_mean,
       color = diff) +
    geom_abline(slope = 1, intercept = 0, color = 'white', size =
          3) +
    geom_point(size = 3) +
    # Compare over square plot with same axis extents makes it
          easier to judge trends
    scale_x_continuous(limits=c(2, 16)) +
    scale_y_continuous(limits=c(2, 16))
```

0.10 Figure composition

```
mpg_weight & hp_weight #Concatenate plots vertically
mpg_weight | hp_weight #Concatenate plots Horizontally
.mark_*().encode(...).interactive() #Panning&zooming
brush = alt.selection_interval()
.mark_*().encode(...).add_params(brush) #IntervalSelections
```

```
plot_grid(hp_weight, mpg_weight) #Horizontally
plot_grid(origin_count, mpg_weight, ncol=1) # vertical
```

0.11 Selection Intervals

```
#Highlighting points with selections
brush = alt.selection_interval(resolve='union') #The default is
      'global' #resolve='intersect'
click = alt.selection_point(fields=['Origin'], on='mouseover')
alt.Chart(cars).mark_circle().encode(
    x='col1', y='col2', color=alt.condition(brush, 'Origin',
          alt.value('lightgray'))
).add_params(brush)
points | points.encode(y='Weight_in_lbs') #Linking selections
      across plots
bars = alt.Chart(cars).mark_bar().encode(
    x='count()', y='Origin', color='Origin',
     opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
).add_params(click)
points & bars #Click selections
```

0.12 Saving plots

HTML can be sent as an email attachment. and still have interactive elements.

```
plot.save('plot.html',scale_factor=3) #python
ggsave('plot-r.png',plot,dpi=96) #R
```