Communicating uncertainties in official statistics — A review of communication methods

EDWIN DE JONGE

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Abstract

This report examines the state-of-the-art for verbal, numerical and visual methods that are available to communicate uncertainties in official statistics reports. It provides insights into the uncertainty of statistical estimates through a review of existing work on the communication of uncertainty, mainly from the perspective of data visualisation (but also touching upon verbal and numerical practices) for describing uncertainty of official statistics. Following the description of various techniques for visualising uncertainty measures, guidelines on choosing an appropriate visualisation method are introduced. The paper concludes that data visualisation is not a mechanical act, being its goal to get the message as clear as possible across, and therefore the final visualisation products for communicating uncertainty depend on the choices related to a series of input parameters (i.e. data pattern, uncertainty measures, prediction and target audience).

Keywords: Data visualisation, Communicating uncertainty, measuring un- certainty, communication tools.

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1 Introduction

1. Introduction

Applied statistics has the aim to produce accurate, precise and valid estimates for the problem at hand, so each statistical estimate should include an indication of its accuracy, precision and validity. National statistical offices produce statistics on the state of a country and communicate these to the general public, as well as policy makers and economic and social scientists. Usually the statistics produced are communicated without an indication of accuracy, precision and validity. This has been noted earlier, as pointed out by Manski (2015), Manski (2019) and van der Bles et al. (2019), headline flash estimates, nowcasts and forecasts are often presented as point estimates, arguably conveying a misleading degree of reliability, without explicitly expressing some underlying and inherent uncertainties. Guides for communicating uncertainty are scarce (Petersen et al., 2013; Mastrandrea et al., 2010) and often have uncertainty of forecasts as their main goal, which includes besides statistical uncertainty also model assumptions. Those scenarios' typically have more sources of uncertainty, since the forecast often are influenced by external factors, which are either not part of the analysis, or are not (yet) known. In this document we will focus on the statistical estimation part and describe forecasting practices when necessary. The present task focuses on the review of existing work that focuses on communication of uncertainty mainly using the field of data visualisation, but will also briefly touch upon verbal and numerical practices for describing uncertainty of official statistics.

2 Why presenting uncertainty?

2. Why presenting uncertainty?

Producing detailed numerical uncertainty indicators in for each different uncertainty category is great from a statistician's point of view, but is commonly thought of as to be confusing for users, especially layman users. Is showing uncertainty not conflicting with the communication of the statistic? How do users perceive representations of uncertainty? Does it affect their interpretation of the data? Does it alter their trust in the institute that produced this statistic? A basic rule in communication (and education) is to tailor your communication to your target audience? Statistical institutes have a broad palette of users: from lay persons to academic users. These users have in common that they are interested in the numbers that are produced by the institute, so a minimal level of numerical literacy can be assumed. In this section we assume numerical literacy, i.e. not statistical literacy, as the lower bound for a user.

2.1. Assessment of uncertainty presentation by users

One common line of thinking is that lay persons do not understand uncertainty or confidence intervals, so that showing them confuses them. How do users perceive the different visualisation methods? Tak et al. (2013) looked at how laypersons can read visualisations of uncertainty, and their findings were positive: most users are able to read uncertainty visualisations and have an understanding of it, be it that users that had some statistical education were more equipped and at ease with indications of uncertainty. The paper also reviewed which types of uncertainty visualisation work 'best', as in, which provide the most accurate reading by users of the uncertainty measure. The well-working methods are error bars and error bands, but to their slight surprise also the 'spaghetti' plots (5). These plots seem to be suited for depicting prediction uncertainty. It highlights that the future is not set, and that there are multiple possible scenario's, some of which are plotted.

2.2. Effect of showing uncertainty on users assessment of data

In the previous paragraph we saw that users can interpret uncertainty presentations and that they do not confuse them. Not being confused is a rather low bar: showing uncertainty show add value for users. van der Laan et al. (2015) studies the effect of showing uncertainty in line and bar charts on users assessment of the data. In their experimental setup they used a synthetic data set and assigned each user randomly to one of 4 groups. The different groups were given the same assessment tasks, but with different presentations of the data: with or without uncertainty, and different variants of uncertainty presentations. An important function of a line chart is to detect if there is an overall trend. When uncertainty of the data was shown, users assessment of the trend was more correct then when the uncertainty was left out. Statistical noise in the data introduces a perceptual bias: users tend to think that the trend is changing while it is not.

An important function of the bar chart is to compare values: is the unemployment for men higher than for women? When uncertainty is shown, users are not confused by it. When the confidence intervals are not overlapping, most users are able to detect which value is higher. When confidence intervals do overlap, users are less secure, and this is a positive finding, since it reflects the statistical uncertainty which of the two values is higher.

2.3. Sources of uncertainty

When discussing uncertainty communication often a breakdown of sources of uncertainty or measurement errors is given: for example uncertainty of a statistic may be the result of the used sampling method, population frame differences, conceptual difference between measured and target variable, model bias or prediction error. Which of these sources are relevant to users depends on their needs and goals, but for almost all users the total or combined error is relevant: how accurate and precise does this official statistic represent the real value? This may be the main reason that uncertainty in graphics is almost never broken done in its components. A second reason is that in many official statistics only sampling errors are taken into account, giving an underestimation of the real uncertainty. The authors do not know any example of uncertainty visualisation, in which different sources of uncertainty are shown, which indicates that users need for broken down uncertainty is limited. In this paper therefore, we restrict ourselves to graphical methods that display ‘just’ uncertainty.

Whether showing uncertainty alters trust in statistical institutes for the better of the worse is not known and is an interesting topic for further research. Depending on the numerical and statistical literacy of its users, showing uncertainty may improve trust in an statistical institute: it makes a statistical institute more transparent. It also allows for more easily updating a statistic with a revised version. Revisions of statistics are typically created when more information is available, and the revised version is more accurate and more certain.

Official Statistics such as GDP, population counts and CPI often have an official status in which they are used in calculations and contracts. Users of these figures often perceive them as exact. Communicating their uncertainty should be delicate, because it could reduce the trust. Helpful in this matter is that the production of those statistics is highly regulated on a European level. Since this production is regulated, the result is trustworthy and comparable to other outcomes, even though they are not as precise and accurate as previously perceived.

3 Verbal communication

3. Verbal communication

Official statistics has been around for long, as population counts in official censuses have been taken place for millennia. The modern incarnation of official statistics was due to the further development of probability theory, statistics and survey methodology. Measurements were known to be imperfect, but good enough for further advancement of government, policymaking and science.

Verbal communication is typically used for forecasting, because the verbal terms describe probabilities. Probabilities are commonly used to describe future events or phenomena. In policy when a forecasting estimate is used, it is important to describe the certainty of the estimate with a verbal indication. A well-known example of forecast are the climate analyses and global temperature forecasts of The Intergovernmental Panel on Climate Change (IPCC). One of the by-products of the IPCC is a document describing how to communicate uncertainty (Mastrandrea et al., 2010).

The following terms are used in the communication of the IPCC (table 1): Noteworthy is that the probability scale is not a linear scale. Verbal communication in official statistics is seldom used, though there is no particular reason not to use it. This may be due to that uncertainty terms are probabilities and most official statistics are estimates of quantities or counts.

Table 1: IPCC verbal uncertainty assessments

Virtually certain	>99%
Very likely	90% – 99%
Likely	66% – 90%
About as likely as not	33% – 66%
Unlikely	10% –33%
Very unlikely	1% – 10%
Exceptionally unlikely	< 1%

4 Numerical communication of uncertainty

4. Numerical communication of uncertainty

The most common communication method for uncertainty in official statistics is numerical communication. Since each figure produced by a statistical institute should have an indication of the certainty, the indications are readily available. Often they are sampling error indications, but can also include other sources of uncertainty.

Some statistical output is pseudo-accurate: the numerical precision of the number is higher than its statistical precision, e.g. the number of farm chicken in 2019 the Netherlands according to Statistics Netherlands was 100 992 944, which seems overly precise. Rounding a statistical estimate to match its statistical precision is therefore a good practice.

Sampling errors are often expressed in standard errors (SE), which is the standard deviation σ of the sampling distribution. When this approximates the normal distribution the true value $\hat{x}$ of statistical estimate $\hat{x}$ lies within $[\hat{x} - 1.96 \cdot \mathrm{SE}, \hat{x} + 1.96 \cdot \mathrm{SE}]$ with 95 % confidence. The 95 % confidence interval is very common in many sciences and official statistics. Other common, but currently less used, uncertainty measures include a Bayesian credible interval and a prediction interval. A credible interval is a summary statistic of a Bayesian data analysis in which the probability distribution of a statistic is estimated. A 95 % credible interval encloses the inner 95 % values of the posterior distribution. A prediction interval expresses the uncertainty of a prediction, which is conceptually different because there is no true value (yet).

Uncertainty measures are available in official statistics but often considered a by-product and not clearly communicated or not expressed at all by the statistical institute. When communicated they are most often not presented together with the statistic but described in a footnote or methodological appendix. Those uncertainty indications are mostly in relative terms: due to sampling errors, the 95 % confidence interval is plus or minus 1 % of its value.

A common practice is to express confidence intervals in percentages of the reported value. While this gives an indication of its uncertainty, it does not communicate the probable range in which the true value lies. A good practice for numerical communication of uncertainty is therefore to present the user an interval with lower and upper bound in the same scale as the statistic itself, e.g.:

Table 2: IPCC verbal uncertainty assessments

2.3 ±5 %	
2.3 ± 0.1	+
2.3 ([2.2, 2.4])	++

Since it shows the range explicitly it does not force a user to do a calculation to achieve the same.

Furthermore, it is more general applicable, since it allows for asymmetric uncertainty intervals, which may be the result of an advanced statistical method.

What the interval exactly represents, a frequentist 95% confidence interval, a Bayesian credible interval or a prediction interval is a statistical detail that depends on the analysis used and should be left to interested reader. For most users, the interval indicates the certainty that the producer of the statistics has found for this statistic.

5 Visual communication of uncertainty

5. Visual communication of uncertainty

Visualisation is a powerful tool for displaying and communicating statistics (Wilke, 2019; Yau, 2013; Meirelles, 2013; Cairo, 2012; Robbins, 2012). The visual perception channel of users of statistics allows for detection of data patterns and abnormalities, such as outliers or missing data with ease (Cleveland, 1987). Often visualisation of statistics provides a dense data summary, summarising and compacting many data into one picture.

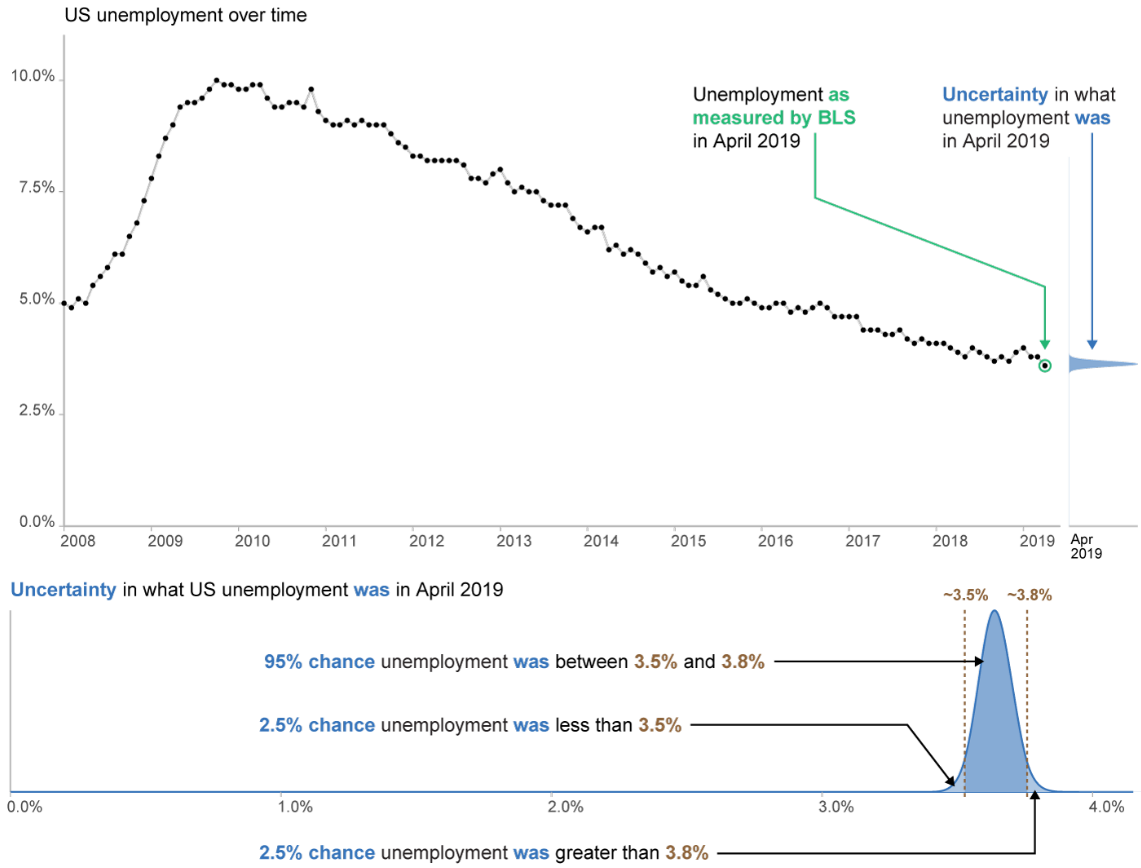
A properly applied visualisation shows the main message of the data, trends or other data patterns, but also reveals subtle details. Visualisation is a promising communication method, for it allows to show the statistical data, but also their uncertainty, by incorporating the uncertainty in the visualisation method.

It is easy to get overwhelmed by statistical details when trying to quantify uncertainty as described by Kapetanios et all (Eurostat SWP, 2020) , or by technical details in reading research on deployments of uncertainty visualisation techniques.

Official statistics often is an estimate of a past phenomenon, in which the uncertainty is in the difference between the estimate and the true population value. This is a different uncertainty than the case where it is a forecast or prediction in which case the uncertainty includes the error of the statistical model. Hullman and Kay (2019) introduces the differences between these concepts with the following example on US unemployment (fig. 1):

The US unemployment is measured by the US Bureau of Labor Statistics on a monthly basis. This measurement is accurate, but not exact, for a large part because the measurement is an estimate based on a sample of total population. The uncertainty in the unemployment can be shown in figure 1. This type of uncertainty, is the uncertainty in what some the unemployment really is or was and is sometimes called reducible: in principle, we could go out and survey every person in the United States to determine their unemployment status, reducing this probability distribution to a single point. In practice, instantaneous measurement is impossible and the duration of measuring introduces uncertainty.

Figure 1: **Uncertainty in statistical estimates (Hullman and Kay, 2019)**



However, some uncertainty is irreducible: if we would predict the unemployment for the next month we can't know exactly for each employee if they are unemployed until that month has passed. While these two kinds of uncertainty are different, both can be described with probability distributions. For example, this is a predictive distribution for the unemployment in May:

Official economic statistics inherently carry uncertainties or errors due to the way they are compiled.

This inherent uncertainty or error can be defined as the difference between the estimated and the true population value. This section critically discusses and reviews different categories and sources of those uncertainties.

Figure 2: **Uncertainty in forecasts (Hullman and Kay, 2019)**

5.1. Uncertainty visualisation methods

In data visualisation data is transformed and mapped onto visual attributes (Wilkinson, 2012). To visualise uncertainty, we need data that expresses the certainty of the estimate numerically, so the input for the uncertainty visualisation method are the uncertainty measures of the statistical output. Basically there are two kinds of measures that are useful for visualising uncertainty: an interval measure and a probability distribution. The interval measures can be a confidence, Bayesian credible or prediction interval. They result from the assumed, estimated or derived distribution of possible values of the statistical analysis.

5.1.1 VISUALISING UNCERTAINTY INTERVALS

An interval measure is by far the most commonly used uncertainty measure in official statistics. It can be a confidence, credible or prediction interval, and includes a level of confidence e.g. 95 %. The uncertainty visualisation thus has to encode the point estimate (the statistic at hand), a lower bound and an upper bound.

Figure 3 shows the most used method in scientific papers of plotting statistical uncertainty: error bar charts. Each point estimate is visualised with a bar, and the confidence interval is plotted as an interval on top each bar. This is a direct encoding the interval and has the benefits that the visual focus is on the point estimate and that the confidence interval is a detail. It follows the same good practice as for numeric communication, that it shows that range of probable values. The error bar makes it also possible to compare the sizes of the intervals for the different estimates. A disadvantage is that the error bar is visually asymmetric, the lower bound is less visible than the upper bound. An error bar is often barely visible, making it a less effective means of communicating uncertainty (Cleveland, 1987). However many academics have been trained in reading plots with error bars, and it is therefore a popular and often used method for plotting uncertainty. Many official statistics are cross-sectional, they allow for comparing a statistic between different sub populations. What is the average salary of a teacher, compared to a doctor? What is the unemployment per region? Bar chart are most often used to visualise these statistics, because they combine showing the absolute value of the indicator as well as make it possible to compare the different values. Since the use of error bars is widely spread it is a good practice to use them for the lack of better visualisation methods for cross sectional uncertainty.

Figure 3: **Bar chart with error bars**

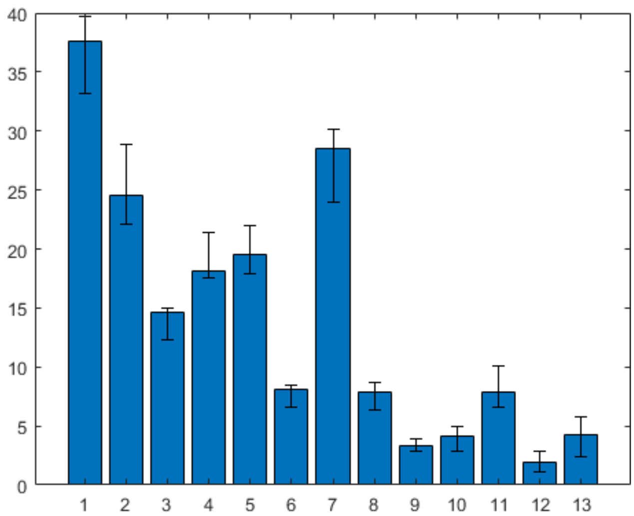
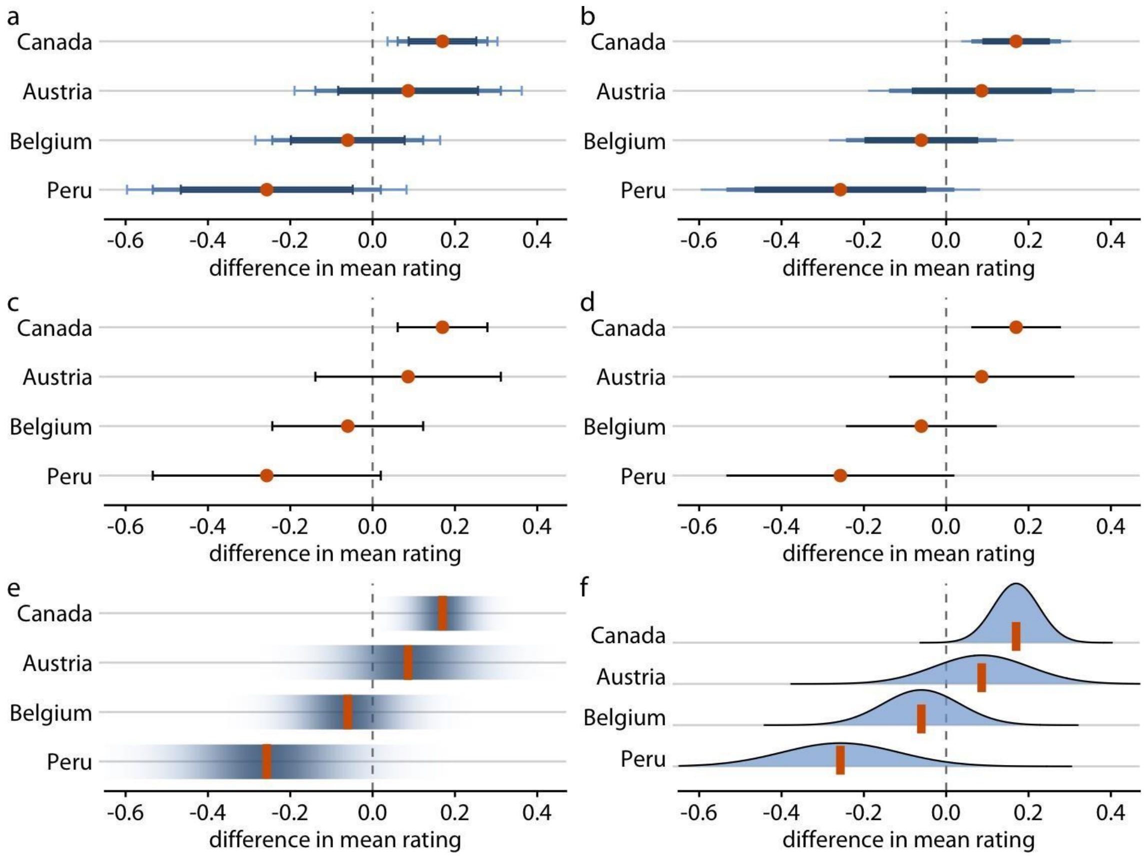


Figure 4 shows various different visualisation methods for confidence intervals, when the main task is comparing different values.

This visualisation supports the user in finding out how the rating for a country differs from the mean rating. The confidence interval visualisation helps to detect how certain the deviation is. Figures 4 c) and d) are standard visualisation methods for interval methods. Figure 4 e) and f) assume anormal distribution, which is common when the interval is a traditional confidence interval. The visualisation methods above are typically used for cross sectional comparison for a fixed reporting period. Another important part of official statistics are time series. For many important indicators it is (more) important to track their development in time. The line chart is the chart that is used to visualise time series. The line connects the subsequent periods, and the y-axis shows the values of the indicator at those different points in time. Figure 5 shows the different options to visually add uncertainty to a line chart from the user study in Tak et al. (2013).

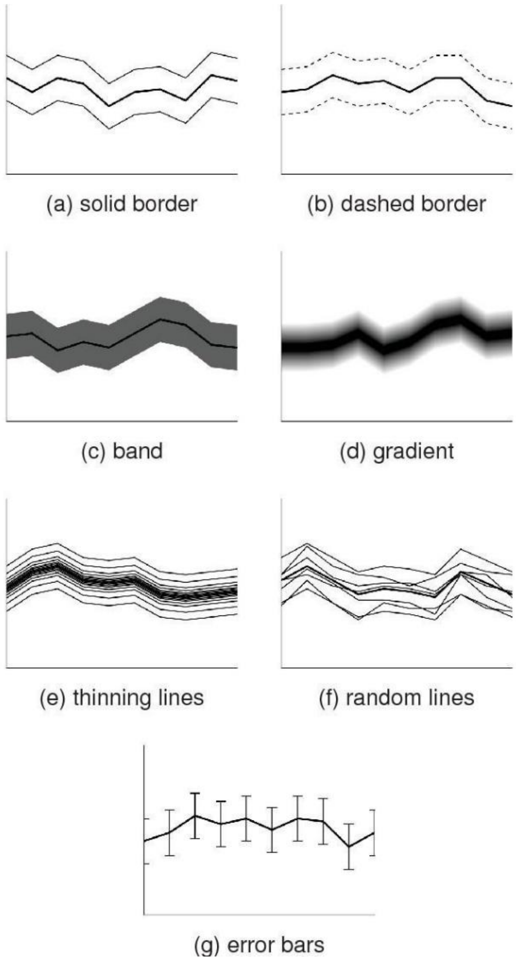
Figure 4: Various confidence interval visualisations from Wilke (2019)



Options a, b, c and g are confidence interval options. All these options ‘work’ for users, but van der Laan et al. (2015) showed that c) and g) are slightly better in reading off the overall trend of a time series. van der Laan et al. (2015) indicate that the error band is most natural to users and can be used as a good practice for showing time series.

Another type of data often to be found in official statistics are proportions, which are often visualised using pie, donut or waffle plots. There are no established visualisation methods that visualise uncertainty in proportions.

Figure 5: **Uncertainty visualisation options for line charts from Tak et al. (2013)**



5.1.2 SHOWING UNCERTAINTY DISTRIBUTIONS

If the result of a statistical estimation is a distribution of values instead of a point estimate, this distribution can be used to display the certainty of the estimation, as shown in figure 7. The distribution can be either a probability distribution, a Bayesian posterior distribution, a predictive posterior distribution or the normal distribution associated with the model error. While traditionally statistical offices restricted themselves to producing point estimates, there are using more and more advanced statistical methods, which produce distributions, that can be plotted.

Box and violin plots (fig. 6) are a visualisation method for plotting distributions for values. They are not well known to the general public, but can be useful for displaying statistical output. For example, the distribution of unemployment per region per gender helps in communicating the distribution of values in the data. The box and violin plot focus on the distribution of values and therefore less useful to depict uncertainty, because there is not point estimate or central point selected.

The uncertainty distribution has to be visually encoded, so users can see how likely the value of an indicator is.

Figure 6: Box and violin plot

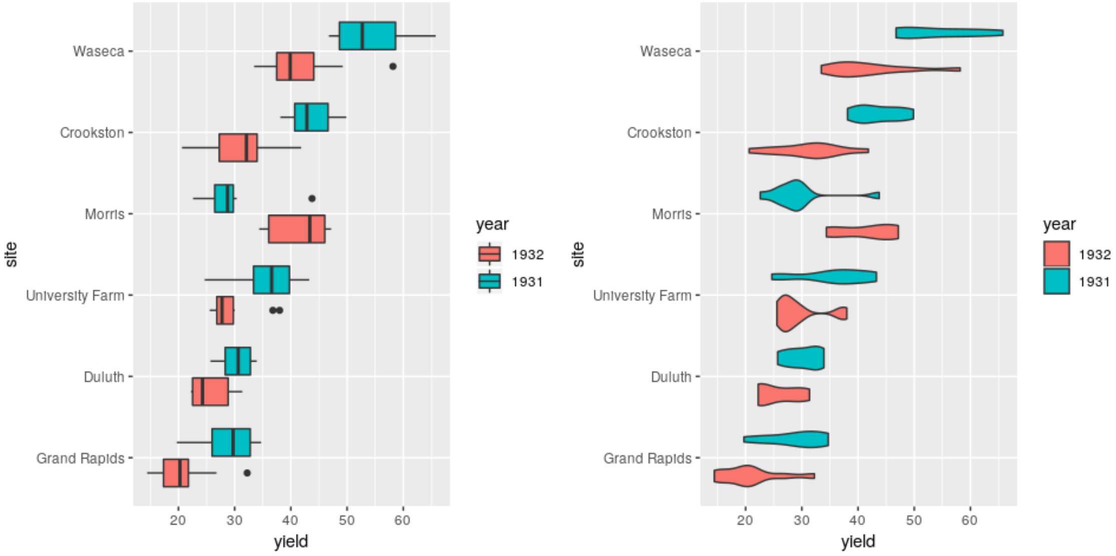


Figure 7 shows various ways to depict the uncertainty. We can use a density plot, which shows the probability of a value.

The gradient approach, where probability is encoded in transparency, the more likely, the less transparent is a popular choice in time series, especially for predictions, as shown in figure 8. The gradient visually stresses that the future is more blurry and unknown, but that some values are more likely than others. Gradient encoding for uncertainty is especially useful in line charts for time series. It can be seen as a finer grained version of the error band, in which not distributional assumptions are made.

For cross-sectional graphs, such as the bar chart, the gradient approach is less suited. In those cases, either a violin plot, or CCDF (fig. 7) plot is more suited.

Figure 7: Visual encodings of uncertainty distribution (Hullman and Kay, 2019)

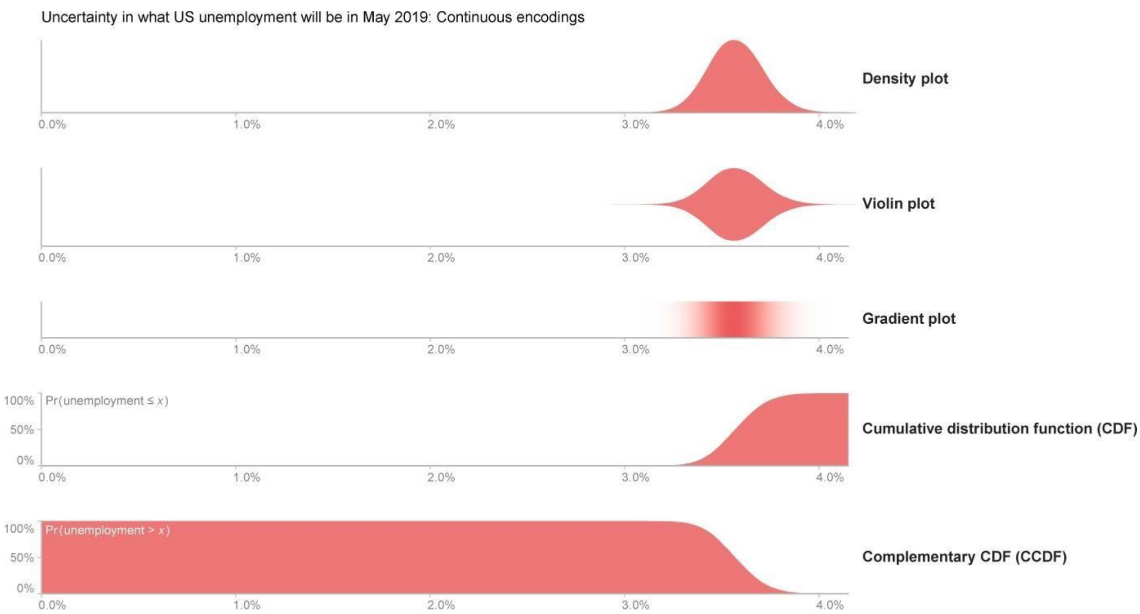
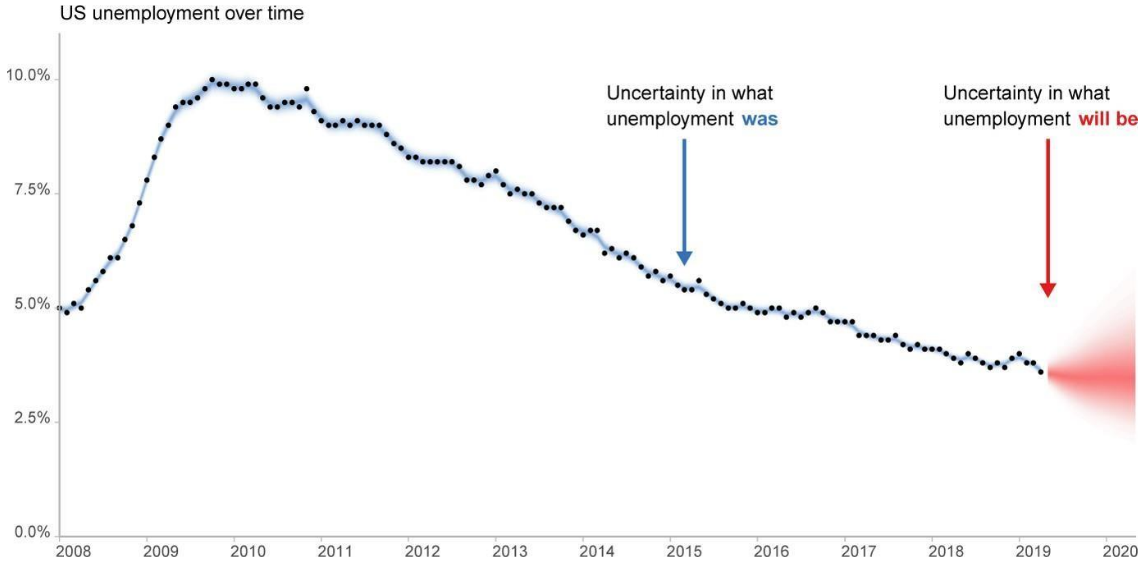
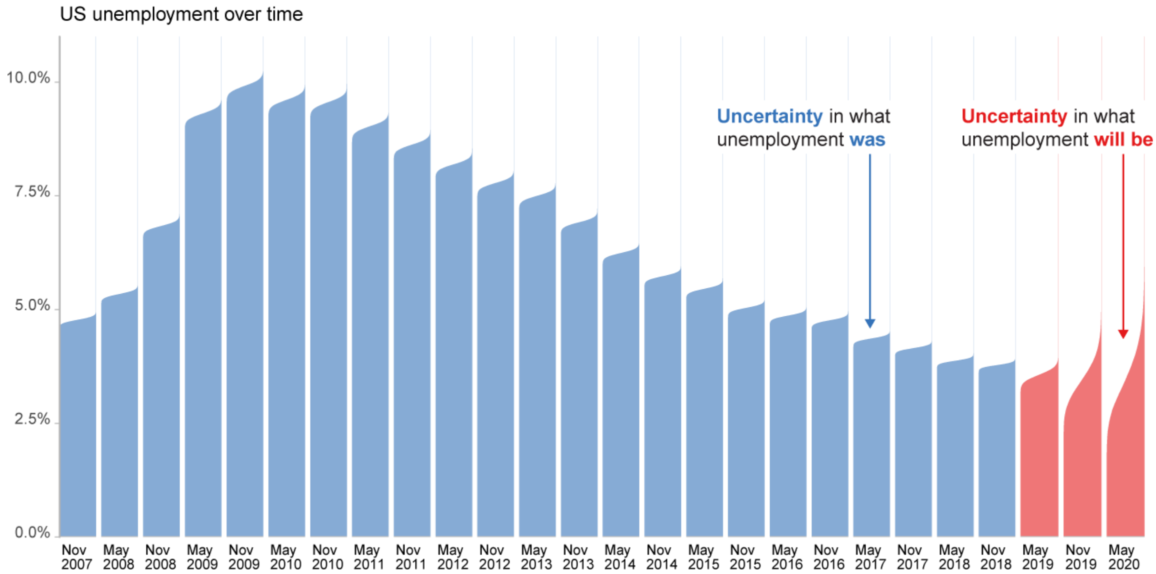


Figure 8: **Prediction uncertainty encoded as gradient Kay (2019)**



The cumulative distribution function (CDF) plot is a statistical plot that is lesser known to the general public. It seems too statistical to be useful for communication, but can be combined with the bar chart and results in figure 9.

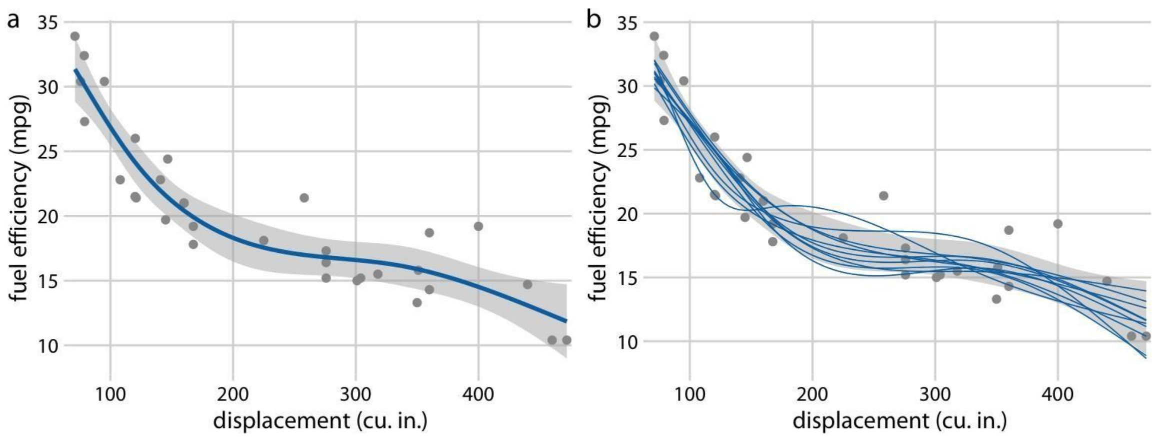
Figure 9: **CCDF enhanced bar chart (Kay, 2019)**



This chart nicely communicates both the size an indicator as well as the uncertainty for each estimate. Each bar is a rotated Complementary CDF. Although this is a new type of chart, it seems to work well in communicating uncertainty, because it is a small adaptation of a well-known chart type.

For showing prediction uncertainty hypothetical outcome plots (HOP), also known as 'spaghetti' plots, can be useful (fig 10). Instead of encoding the distribution, a hypothetical outcome plot shows multiple possible scenario's or outcomes.

Figure 10: **Hypothetical Outcome Plot (Wilke, 2019)**



The HOP works by making explicit that the future (or estimation) is not set, and that one of multiple outcomes is possible. Although the hypothetical outcome plot does not encode the full uncertainty distribution, in practice it works well to communicate uncertainty as noted by (Tak et al., 2013; Hullman and Kay, 2019).

6 Visualisation recommendations

6. Visualisation recommendations

This report describes various techniques on visualising uncertainty measures. We provide some guidelines on choosing an appropriate visualisation method.

First, when uncertainty measures are available for the data to be presented, these should be incorporated into the chart as far as possible.

The choice depends on the following ingredients: data pattern, uncertainty measure, prediction and target audience.

- A well-chose chart type communicates a specific data pattern; e.g. a line chart communicates the development over time of a statistic, a bar chart communicates the comparison of sizes and a point chart communicates differences in value.
- What uncertainty measure is available? Is it an interval or a distribution?
- Are the data the result of an estimation or a prediction?
- Is your target audience statistically literate?

The first choice is a general visualisation recommendation. The appropriate chart type needed for communicating the pattern in the data should be chosen. The following table shows recommendations for chart types described in this report for the different choices:

Data pattern	Uncertainty measure	Estimation/ prediction	Audience	Chart type
development	interval	estimation/ prediction	general	line + band (fig. 5c)
development	distribution	estimation	general	line + gradient (fig. 5d)
development	distribution	prediction	general	line + gradient (fig. 5d), HOP
				(fig. 5f, 10)
comparison	interval	estimation/ prediction	general	bar + error bar (fig. 3)
comparison	distribution	estimation/ prediction	general	bar + CCDF (fig. 9)
differences	interval	estimation/ prediction	general	point + error bar (fig. 4c, 4d)
differences	distribution	estimation/ prediction	general	point + gradient (fig. 4a, 4b, 4e)
				point + distr (fig. 4f)
differences	distribution	estimation/ prediction	statistical	box/violin plot (fig. 6a, 6b)

n.b. the statistical literate audience is included in the general audience (and not vice versa)

It should be noted that these are only guidelines: data visualisation is not a mechanical act, its goal is to get the message as clear as possible across. These recommendations can be diverged from when necessary.

7 Conclusion

7. Conclusion

This report introduced several methods for displaying the uncertainty measures. Leaving out uncertainty in statistical graphics is current practice in many official institutes. Contrary to commonly thought research indicates that laypersons are able to ‘read’ uncertainty visualisations and that users’ assessment of data is better. Communicating uncertainty in statistical visualisations therefore adds value to users and clarifies that statistical offices produce statistics. Visual methods for presenting uncertainty are readily available as seen in section 5. When more advanced statistical methods are used that result in distributions (instead of point estimates) new visualization methods have been developed, such as HOP and CCDF bar chart.

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Communicating uncertainties in official statistics — A review of communication methods

This report examines the state-of-the-art for verbal, numerical and visual methods that are available to communicate uncertainties in official statistics reports. It provides insights into the uncertainty of statistical estimates through a review of existing work on the communication of uncertainty, mainly from the perspective of data visualisation (but also touching upon verbal and numerical practices) for describing uncertainty of official statistics.

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