Reporting about Diversity and Inclusion that Inspires to Action — DRAFT

A White paper for the R-library "div"

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Abstract

In this paper we present a extensive framework to report on quantifiable outcomes of diversity and inclusion. The aim is to create a framework that is inclusive in itself and directly inspires to action. To achieve these two goals, we first develop a diversity measure and then then a reporting that allows to identify inclusion by measuring outcome (such salary, time to promotion, etc.).

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1 Introduction

No business or team can thrive without a motivated team to get the job done[1], and if you are reading this then changes are that you have read books like Zaroda-Dabrowska and Dabrowski 2019 and are working on making your workplace a more diverse and inclusive environment. If you are serious about diversity and inclusion, then this paper together with the R library `div` will help you to identify areas where improvement will make the most impact. This paper is however not a manual for the software library but rather a document that describes the choices that we have made in the library `div` as well as the reasoning behind those choices.

1.1 The case for diversity

Similar to biological evolution "it is not the most intellectual of the species that survives; it is not the strongest that survives; but the species that survives is the one that is able best to adapt and adjust to the changing environment in which it finds itself"[2]; a commercial company needs to be able to adapt to the ever changing landscape of customers, stakeholders, technology, raw material, geo-politics, etc.

It seems logical that being adaptable is more obvious if the team is more diverse and brings more perspectives to the table. For example, McKinsey & Co. has published about correlation between gender diversity and financial performance, and they find that "companies with more diverse top teams were also top financial performers" — see Barta, Kleiner, and Neumann 2012. However, these studies do not prove a causal relationship. The paper phrases it as follows: "We acknowledge that these findings, though consistent, aren't proof of a direct relationship between diversity and financial success."

Most studies that look for correlation between diversity and performance fail to prove a causal link. Some attempts to include a control variable actually show that this control variable can also explain the results. For example, Badal and Harter 2014 use the controlling variable "employee engagement." They find that both gender diversity and this employee engagement independently are able to "explain" the financial success of a company.

In summary, while there is ample evidence that diversity can accompany performance, there is no evidence for a causal link. However, the logical argument based on biological evolution –as previously presented – still holds. Also it can be argued that bias in decision making inevitably leads to sub-optimal decisions.

[1] In this paper we will not elaborate on forging strong teams as such, instead we warmly recommend Lencioni 2002 and Marquet 2015 to get started.

[2] While usually attributed to Charles Darwin, and most certainly inspired by his work, we could not find any trace of this citation in his works. The earliest reference appears to be from Leon C. Megginson: June 1963, Southwestern Social Science Quarterly, Volume 44, Number 1, "Lessons from Europe for American Business by Leon C. Megginson", (Presidential address delivered at the Southwestern Social Science Association convention in San Antonio, Texas, 12 April 1963), Published jointly by The Southwestern Social Science Association and the University of Texas Press.

1.2 The case for inclusion

It seems obvious that if we want to reap the benefits of differences in thinking that it is necessary that everyone that constitutes that diverse team feels comfortable to speak up. This is the essence of the economic argument for inclusion.

For example, the the MBTI profiles use as third dimension the dichotomy “judging/perceiving”. The labels are somehow misleading and actually means something like “needs plans vs needs spontaneity”. Both profiles are able to see each others point of view and argue about it but both will have the innate first reflex to make a plan (“judging”) or just go for it (“perceiving”). This is a valuable difference as it lays the foundation to discuss in the team the right approach for the situation at hand. This is the essence of strong teamwork. See for example Lencioni 2002.

So, it is obvious that both people should feel able to speak up and even while the whole team has the tendency to start planning, the perceiver should have the chance to speak up and make his or her case. It is essential to weight both perspectives for each project or challenge.

While diversity is something that can be decided by a limited group of decision makers[3], inclusion is something that must be borne by everyone in the team. In order for each person to feel included, it is necessary that each other person provides the cover and comfort. Inclusion is about feelings and hence way more difficult to achieve. The team leader can steer in that direction in order to build a strong, diverse and inclusive team that focuses on results. However, this cannot work without everyone contributing to it.

This feeling of being included can be measured by targeted surveys that map the feeling of being able to realize potential, being included, listened to, etc. to dimensions such as belonging to a social group and having a certain personality type (as in MBTI and/or the big 5).

While these types of insight are valuable they can be complemented by measuring output in terms of salary-bias, promotion-bias, etc. Such quantitative analyses provides other insights. For example a salary or promotion bias can be the result of unconscious/passive bias. It is indeed possible that while everyone if welcoming and an inclusive climate reigns that a certain group is systematically underpaid relative to another group.[4]

In this paper we will elaborate how to create a meaningful and actionable reporting based on the quantifiable outcomes such as salary, bonus payments, promotion chances, etc. in Section 4.

1.3 The case for measuring outcome and KPIs

For any business, for any company, for any manager, for any team, and for any individual employee having a ”scorecard” or ”a set of KPIs” this is a powerful idea. In the first place, it helps to create clarity about what is to be done, but most importantly the author’s adagio ”what you measure is what you get” always seem to hold. Measuring KPIs and discussing them aligns minds and cre-

[3] For example the hiring manager can hire a diverse pool of people. That is only his/her decision.

[4] The opposite is also possible: for example there is no pay-gap but a certain group is not listened to. So both approaches have their own merits and we recommend to do both.

ates a common focus. If the manager measure sales per quarter, then your staff will pursue sales at any cost and converge towards a short time perspective. If the manager has a place on the scorecard for "feedback from the customer," then employees will converge towards entirely different values and value sustainable, long-term results.

A scorecard should be simple (say each employee should focus on maximum seven personal KPIs), but also offer enough detail to find out when things go wrong and ideally offer enough detail to get us started when investigating mitigating measures.

A scorecard that has SMART goals (goals that are specific, measurable, attainable but realistic and limited in time) also creates a moment to celebrate success. This is another powerful motivator for any team!

The underlying mechanics of dashboards also apply to any other aspect of any business: from showing what happens in a production line, over what customers are profitable to what competitors are doing. Using a scorecard will create clarity about what is done and people will strive for it.

In the remainder of this chapter we will show how to build a simple dashboard. To focus the ideas we will create a dashboard that is about diversity of employees.

2 Are we all biased?

It is a well understood and commonly accepted fact that the human mind is biased. For example Russo and Schoemaker 1989 argue that the main barrier good decision making are biased heuristics in the mind. Some of the most disturbing and clear forms of bias are related to:

- **Overcondidence on own ability and own judgement**: we systematically over-estimate our own abilities (e.g. After the failure of LTCM the owners tried many more hedge funds that equally failed) – typically people use the wording "to be sure" when they are actually 85% sure — See: Camerer and Lovallo 1999; Daniel, Hirshleifer, and Subrahmanyam 2001.

- **Framing** we systematically fail to consider problem from multiple points of view (frames), more in particular we tend to focus on a small frame (e.g. profit and loss of an investment) and fail to see the bigger frame (total wealth) — See e.g. Tversky and Kahneman 1981

- **Confirmation Bias**: we tend to neglect information that dis-confirms our beliefs and overweight information that confirms our beliefs —

- **Information Bias**: the more information we have, the more confident we get; however, in reality too much information is basis for a weaker decision process. This overconfidence translates in believing that we can "win it" and we fail to follow a process —

- **Groupthink**: we have the innate need to conform (e.g. notice how hard it is to remain seated when everyone else is going for a standing ovation), this results in the belief that the majority is right —

- **Shortsighted Shortcuts**: this leads to underestimating the risk of a viral outbreak or interest rates. It also results in trusting that our brain has an unbiased view on the world. Instead our brain will typically use the most readily available information as an anchor and extrapolate from there (but not enough – aka Anchoring) —
- **Attribution Bias and Failure to Seek Feedback**: when a decision is successful then we tend to attribute the success to our own abilities (e.g. "I'm a good investor since the stock that I bought is up") and failures to external circumstances (e.g. "the stock that I bought is down, because of an unfortunate decision of the FED") —
- **Tribal Thinking**: we tend to use ourselves as the norm to judge others and tend to see what our tribe does as normal. An interesting example are the Latin words "dexter", and "barbarus"[5] Obvious examples are wars between tribes, nations, or within nations: almost without exception the rivalling party is portrayed as barbarian.
- **Failure to Learn**: even when we get the feedback, it seems hard to adjust our decision process or understand the biases and heuristics that govern our decision process —
- **Herd behaviour**: our innate drive to conform to the group to which we belong, to fit and to be part of a group (in a way, group-think is a special case of this bias) – Banerjee 1992; Nosfinger and Sias 1999
- **In-group favouritism**: related to the previous, and also known as in-group–out-group bias, in-group bias, intergroup bias, or in-group preference, is the bias to favour members of one's in-group over out-group members. This results in an automatic bias for own gender (Rudman and Goodwin 2004) and race (Fershtman and Gneezy 2001). We have the tendency to self-identify with groups and favourise members of them in many ways – Sumner 2007; Oklahoma. Institute of Group Relations and Sherif 1961

There is indeed ample evidence that we all are biased. Even the manager who honestly tries to forge strong and diverse teams, and fosters an inclusive atmosphere has many psychological biases that hinder rational decision making. Nobody is free from bias and we are influenced by who we are as well as by our environment. Our brain is evolved to do pattern recognition, and just as machine learning that will pick up patterns that might be true (or true in our distorted perception of the world) on average, but forego the right of everyone to be treated as an individual. Even with the best intentions, each one of us will have certain biases: both active and passive. Active bias is where one holds an explicit or implicit bias and hence will automatically value people more based on that bias. To get you started, we refer to two possible places where you can test for your own biases:

[5]The word "dexter" means left, wrong, unfavorable, on the left hand, perverse, harmful: it was indeed the norm to write with the right hand. Also in English "right“ revers to the direction on the right but is also the word to indicate what is fair according to the judicial system. "Barbarus" referred originally to foreigners but soon became a word that indicates uncultivated, savage, uncivilized, wild, cruel, etc.

- tolerance.org
- Harvard University

Besides being conscious or uncounscious, bias can also be active or passive. Active bias would be that you believe that a certain group is better in a certain job and hence you pay them more. Passive bias occurs where a person makes biased decision while the intend was to be unbiased. This is because other people will push your decision making in a certain direction.

For example of you have two employees and a small budget for salary increase. Whom would you give the money to? To the person that complains or to the person that expresses concern about your difficult task as a manager. Who on average would be these people? Well women score on average higher in agreeableness and are more "feeling" – in MBTI terminology – so you can expect on average men to be more vocal about their salary expectations and women to be more inclined to express compassion. This mechanism will push you to give salary increases –on average– more to men then women.

To get you started on the subject of psychological traits and differences, we refer to the MBTI profiles or the – more recent and more scientific – "theory of the big five personality traits". The Big-5 theory identifies five factors:

- openness to experience (inventive/curious vs. consistent/cautious)
- conscientiousness (efficient/organized vs. extravagant/careless)
- extroversion (outgoing/energetic vs. solitary/reserved)
- agreeableness (friendly/compassionate vs. challenging/callous)
- eroticism (sensitive/nervous vs. resilient/confident)

In both theories men and women are typically[6] different. For example in the Big Five one finds that women score higher on extroversion, neuroticism, and agreeableness. The combination of those two last dimension implies that men will be (on average) more confident and less likely to accept that there is no salary rise for them. Therefore men will be more likely to ask promotion and salary increase and will therefore also be more likely to obtain it.

So, if you want to make unbiased decisions, you will need to:

1. understand what biases you have
2. understand what psychological traits you have an how they appear statistically in different groups of society, and
3. measure objectively where it all brings you.

What we offer with the library `div` is reporting that helps you with the last point: it identifies possible areas where bias would have influenced the salaries (or other rewards) in your team. Such statistical approach does not claim to understand the bias, but presents the analyses on such way that it becomes **actionable**.

[6] Typically means here "on average". For example in the MBTI profile, we find that roughly 60% of males are "Thinking", where 60% of females are "Feeling". More information about the MBTI profiles is for example on wikipedia.or or www.myersbriggs.org.

3 Measuring diversity: the Diversity Index

What could be more natural measure for diversity than Boltzmann's definition of entropy? In 1877, he defined entropy to be proportional to the natural logarithm of the number of micro-states a system could potentially occupy. While this definition was proposed to describe a probabilistic system such as a gas and aims to measure the entropy of an ensemble of ideal gas particles, it is remarkably universal and perfectly suited to quantify diversity.

This definition is also used in De Brouwer 2020.

Under the assumption that each micro-state is improbable in itself but possible, the entropy S is the natural logarithm of the number of micro-states Ω, multiplied by the Boltzmann constant k_B:

$$S = k_B \log \Omega$$

When those states are not equally probable, the definition becomes:

$$S = -k_B \sum_i^N p_i \log p_i$$

Where there are N possible and mutually exclusive states i, with their associated probability of p_i. This definition shows that the entropy is a logarithmic measure of the number of states and their probability of being occupied.[7]

If we choose the constant k_B so that equal probabilities yield a maximal entropy of 1 (or in other words $k_B := \frac{1}{\log(N)}$) then we can program in R a simple function.

In the context of diversity, entropy works fine as a measure for diversity. Many authors use a similar definition.[8] In this section we will take a practical approach.

If there is a relevant prior probability (e.g. we know that the working population in our area consist of 20% Hispanic people and 80% Caucasian people) then we might want to show the maximum diversity for that prior probability (e.g. 20% Hispanic people and not 50%).

In such case, it makes sense to rescale the diversity function so that a maximum is attained at the natural levels (the expected proportions in a random draw). This can be done by scaling $s(x)$ so that the scaled prior probability of each sub-group becomes $\frac{1}{N}$. So, we want for each group i to find a scaling so that

$$\begin{cases} s(0) &= 0 \\ s(P_i) &= \frac{1}{N} \\ s(1) &= 1 \end{cases}$$

with P_i the prior probability of sub-group i. For example, we could fit a quadratic function through these three data-points. A broken line would also work, but the quadratic function will be smooth in P_i and has a continuous derivative.

[7]Note also how similar entropy is to the definition of "information entropy" – the formula is the same: $I = -\sum_i^N p_i log(p_i)$.

[8]See for example Jost 2006, Keylock 2005, Botta-Dukát 2005, Kumar Nayak 1985, or De Brouwer 2020.

Solving the simple set of aforementioned equations, we find that $s(x)$ can be written as:

$$s(x) = ax^2 + bx + c,$$

where

$$\begin{cases} a &= \frac{1-\frac{1}{NP_i}}{1-P_i} \\ b &= \frac{1-NP_i^2}{NP_i(1-P_i)} \\ c &= 0 \end{cases}$$

with N the number of sub-groups and P_i the prior probability of the group i.

To add this as a possibility but not make it obligatory to supply these prior probabilities, we re-write the function ‘diversity()‘ so that it takes an optional argument of prior probabilities; and if that argument is not given, the function will use the probabilities as they are.

Note that this quadratic scaling will not always work. In general it fails when the prior probabilities are too far from 50/50 (more than 75/25). In that case we recommend a linear scaling.

For example, if we have prior probabilities of three subgroups of 10%, 50% and 40% then we consider our population as optimally diverse when these probabilities are obtained:

```
# Consider the following prior probabilities:
pri <- c(0.1,0.5,0.4)

# No prior priorities supplied, so 1/N is most diverse:
diversity(c(0.1,0.5,0.4))

## [1] 0.8586727

# The population matches prior probabilities, so index should be 1:
diversity(c(0.1,0.5,0.4), prior = pri)

## [1] 1

# Very non-diverse population:
diversity(c(0.999,0.0005,0.0005), prior = pri)

## [1] 0.002478312

# Only one sub-group is represented (no diversity):
diversity(c(1,0,0), prior = pri)

## [1] 0

# Numbers instead of probabilities provided, also this works:
diversity(c(100,150,200))

## [1] 0.9656336
```

We can also visualize what this function does. For example, assume prior population of men and women equal and consider gender as binary, then we can visualize the evolution of our index as follows – the plot is in Figure 1:

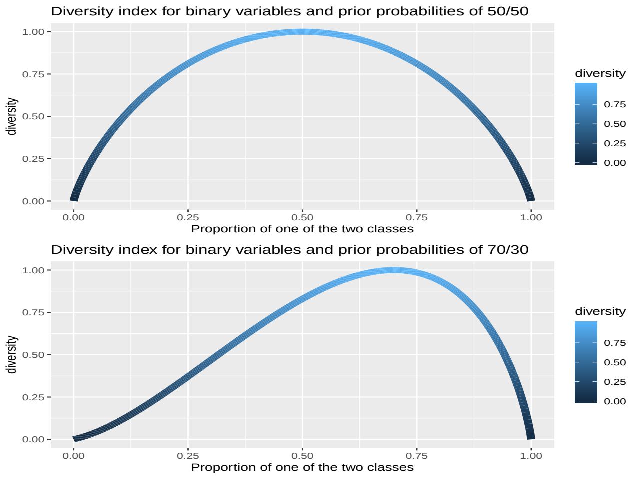

Figure 1: The diversity index illustrated for the case where there are only two possible classes (e.g. in the case of binary sex), and where the prior priorities are respectively 50/50 (top) and 70/30 (bottom). This shows how the index reaches a maximum at a distribution equal to the prior probabilities.

4 Inclusion and gap information

4.1 The paygap as a measure of inclusion

While diversity is rather easy to measure with a diversity index, inclusion is a more elusive concept. While we admit that much progress can be made here, it seems that there are two major – and probably complementary – approaches:

- **try to quantify qualitative quantities**: check inclusion via surveys and demographic data (e.g. ask a set of questions that check inclusion and cross reference that with known or asked data such as belonging to a minority group); and
- **use a variable that is quantitative in nature and informs about inclusion, and cross reference that with an objective factor variable**: for example do people get equal pay for equal work.

In previous section we have demonstrated that certain biases will lead to unequal pay if not measured. This can even occur when the manager is the most inclusive person and has all the best intentions. For example, men are less "agreeable" and more prone to speak up if they are unhappy about their salary – this might lead to allocating higher pay to men. Similarly an unconscious bias in favour of a certain group might lead to higher pay for that group.

In the remainder of this paper we will focus on pay as the variable and use various factor variables such as gender, age, etc. to cross reference.

Definition 4.1 (pay-gap)**.** *A pay-gap for group A is defined as the quotient of medians of salaries in group A and those not in group A for a given seniority* *level and job category.*

$$Paygap = \left.\frac{median(salary\ of\ people\ in\ group\ A)}{median(salary\ of\ people\ not\ in\ A)}\right| Seniority\ S\ and\ Job\ J \quad (1)$$

Note that the definition assumes that there is a categorical variable that defines group A. For gender this could be our population of males or females. However, this definition is always open to have more groups.

The reason to choose for median and not mean is that the median is not sensitive to outliers. This is important because if outliers are taken into account managers will tend to assume that the outcome is what it is because of some outliers that are fresh in mind (see also Anchoring Bias). In other words, by using the median we cannot accept outliers as a valid argument for a result significantly different from one.

4.1.1 The Mann-Whitney U test

When calculating the means of two sub-populations, it is almost inevitable to find differences. The important question is: "what confidence do we have that this deviation is not due to random effects". This answers can be determined via the Mann-Whitney U test.

The Mann–Whitney U test (also known as Mann–Whitney–Wilcoxon (MWW), Wilcoxon rank-sum test, or Wilcoxon–Mann–Whitney test) is a non-parametric test of the null hypothesis that, for randomly selected values x and y from two independent populations, the probability of x being greater than y is equal to the probability of y being greater than x (in other words that the medians of both stochastic variables X and Y are equal.[9]

For a small number of observations (as we have here) one can take an observation of X and see how many times an observation of Y is bigger, then repeat for all x and count how many times the the population of X has a higher outcome (or lower). Count 0.5 in case of ties, and hence we have U_x and U_y (resp. the number of wins for X and Y).

This U statistic allows us now to calculate a "p-value". The p-value is the probability that we make a mistake when rejecting the zero hypothesis (that both medians are equal). So a small p-value corresponds to a high certainty that there is indeed a systematic difference in salary between the two considered sub-populations.

4.1.2 Adding color to the paygap information

It follows from Definition 4.1 that paygap is a positive number that equals one for equal pay. However, it is not obvious what level of paygap indicates that this is the result of bias and not a result of a random selection. It is indeed possible that by pure chance a paygap could be 1.2, and there might be an objective reason why this is the case.

[9] Note that this test is related to a similar non-parametric test used on dependent samples is the Wilcoxon signed-rank test. Dependent populations means that each observation of X is related to one of Y (e.g. the temperature in two different cities measured on the same days). The ladies and men are in this sense independent populations

We can now use the knowledge of the p-value (see Chapter 4.1.1) to provide a level of confidence to a given paygap. We then use this p-value to assign a number of stars and eventually RAG colouring as per the table below (where "p" is the p-value).

- 'paygap' = the ratio of median salaries of one group divided by the median of the salaries of the other group
- 'NA' = numbers are too small, please look at individuals;
- nothing = no bias detectable — $p > 0.1$;
- '.' = maybe there is some bias, check individuals — $0.05 <= p < 0.1$;
- '*' = you should check for bias — $0.01 <= p < 0.05$;
- '**' = bias is probably there — $0.001 <= p < 0.01$;
- '***' = most certainly there is bias — $p <= 0.001$

4.2 Propensity at promotion

Beside salary, bias can also manifest itself in bonus payments, promotion chances. Bonus payments can obviously be treated similar to salary (as elaborated in previous section, Section 4.1).

Also dates of last promotion will be available in the HR system and hence we can use this date to calculate a number of years in the same grade. This number of years can then be used similar to the salary and all mathematics developed in previous section will still hold.

The time in given grade can be used as such or one could use $\frac{1}{time\ in\ grade}$ as proxy for "propensity to be promoted". The advantage of this approach is that the adagio "higher is better" is holds.

5 What course of action is best?

5.1 Targets on diversity

There is still a lot of room to research the link between diversity targets and performance as well as their long-term effects.

There are studies that find a positive correlation between diversity and performance (e.g. Hunt, Layton, and Prince 2015, Altiner and Ayhan 2018, as well as the overwhelming majority of the papers in the survey Urwin et al. 2013), while others find a negative correlation (e.g. Jonson et al. 2020).[10] This last one is particularly interesting as it demonstrates that older boards have better performance than younger boards. So it is unwise to strive for age diversity at board level, but the authors also find that females on high positions are on average younger. So, while females do not innately perform worse than men,

[10] It is important to understand the difference: Jonson et al. 2020 finds that older boards perform better, but Altiner and Ayhan 2018 finds that more diverse software teams perform better (that includes age, gender, ethnicity, but diverse schooling background makes the most impact.

the diversity targets force companies to promote females faster. The lack of experience will then backfire on the performance of the team, the result might also be bad for female colleagues.

While most studies, find positive correlation between diversity and performance; it seems that the performance gains can also be explained by other factors (see e.g. Senichev et al. 2013). It is of course obvious that diversity, without inclusion is worthless and it also makes sense to manage that diversity properly (as suggested by Riccò and Guerci 2014).

In any case those studies study the correlation between performance and diversity and not study the relation between performance and the fact that one uses targets on diversity as a tool to achieve targets.

There is no evidence that targets on diversity do any good – apart from making the stubborn middle manager focus on achieving it – but there is evidence that targets on diversity as such are detrimental. Hence we do not recommend to have KPIs to achieve a certain form of diversity. This is bound to lead to discrimination, which in turn will backfire against the group that is being favoured.

However, in the case that the company fails to get traction otherwise, it KPIs on diversity are an easy start: it requires only the engagement of the hiring manager, is easy to measure, and it will get the debate started.

We do recommend, however, to measure diversity and consider it as an outcome in progress on inclusively. The trend in the diversity provides valuable information.

5.2 Targets on inclusion

We were unable to find literature that links inclusion to corporate performance. However, if we consider engagement as a proxy for inclusion, then there is plenty of studies that all underline employee engagement as a key factor in performance – for example: Markos and Sridevi 2010

There is also research that links employee engagement to CSR (Albdour and Altarawneh 2012), and there is also evidence that CSR is conducive to good corporate results.

In any case we argue that inclusion should be an important direct target, since without inclusion it is impossible to have true teamwork where the diversity of thought can be utilised.

5.3 Actions based on the gap-reporting

We recommend to action in the first place the results of a gap analyses for pay, bonus, and promotion probability. The action list that can be derived from such analysis, will help to de-bias the managers, create a more inclusive atmosphere and eliminate doubt that hidden discrimination reigns.

6 Conclusions

While targets on diversity can have negative side effects and are in their nature discriminatory, we recommend to focus on inclusion as a driver to obtain that diversity as a result.

The simple approach to measure statistical significance of earnings and promotion chances for different groups is powerful. We argue that our approach is:

1. **inclusive**: instead of focusing on a one group only (e.g. females and talk about the "percentage of females") we present an approach that can work for a number of groups and a number of dimensions (e.g. gender, nationality, age, etc.)
2. **flexible**: this method requires only data that each company will have and this method can be used for categorical data (e.g. genders) and continuous variables (e.g. age or time in the firm)
3. **to the point**: instead of using the average salary of males and females in the firm, we filter per grade and job category. This assures that we measure a paygap and not a "occupation gap."
4. **actionable**: this is probably the most important argument. The information is presented in such way that it becomes possible to take action.
5. **simple**: we only use data that is available in most HR payroll systems.

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