

**How to Gauge Inequality and Fairness:  
A Complete Description of  
All Decomposable Versions  
of Theil Index**

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## 1. Need to gauge inequality and fairness: a general problem

- More and more decisions are made using AI.
- So, it becomes more and more important to make sure:
  - that these decisions are fair, and
  - that these decisions do not result in an increase in inequality.
- To be able to do that, we need to gauge inequality and fairness.
- In general, if we have  $n$  people with incomes  $x_1, \dots, x_n$ , then, based of these values, we can find the average income

$$\bar{x} \stackrel{\text{def}}{=} \frac{x_1 + \dots + x_n}{n}.$$

- How can we gauge the inequality, the fact that some incomes differ from the average: some are larger and some are smaller?

## 2. Statistics' answer to this question

- In statistics, the usual way to measure the deviation from the mean is by using sample variance  $V = \frac{1}{n} \cdot \sum_{i=1}^n (x_i - \bar{x})^2$ .

- Practitioners also use variance's square root, standard deviation

$$\sigma \stackrel{\text{def}}{=} \sqrt{V}.$$

- The standard deviation  $\sigma$  provides the *absolute* value of the deviation, in the same monetary units as the income itself.
- To get the *relative* values – e.g., in percents – we can divide  $\sigma$  by the mean  $\bar{x}$ .
- The resulting ratio is known as the *coefficient of variation*

$$CV \stackrel{\text{def}}{=} \frac{\sigma}{\bar{x}} = \frac{\sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (x_i - \bar{x})^2}}{\bar{x}}.$$

### 3. Statistics' answer to this question (cont-d)

- We can somewhat simplify this expression if we divide both the numerator and the denominator by the mean  $\bar{x}$ .
- Then we get the following simpler expression:

$$CV = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (r_i - 1)^2}, \text{ where we denoted } r_i \stackrel{\text{def}}{=} \frac{x_i}{\bar{x}}.$$

## 4. Good news: standard deviation is decomposable

- Often – e.g., after each census – we need to process a lot of information.
- Nowadays, it is possible – and being done:
  - to move the information about all 300 million people to a single location and
  - to process this information.
- But even now, this is not computationally easy.
- In the past, it was not possible.
- However, it was always possible to compute the mean and the standard deviation for income – and for all other characteristics.
- The reason is that these characteristics are *decomposable* in the following sense.

## 5. Good news: standard deviation is decomposable (cont-d)

- Suppose that the sample  $N = \{1, \dots, n\}$  is divided into several disjoint sub-samples  $N = N_1 \cup \dots \cup N_m$ , so that

$$N_j \cap N_{j'} = \emptyset \text{ for all } j \neq j'.$$

- Suppose that for each sub-sample  $N_j$ , we know the number of elements  $n_j$  and the mean  $\bar{x}_j = \frac{1}{n_j} \cdot \sum_{i \in N_j} x_i$ .
- Then this information is sufficient to compute the overall mean, there is no need to also use the original values  $x_i$ .

## 6. Good news: standard deviation is decomposable (cont-d)

- Indeed, the overall mean is the ratio of the overall sum and the overall size  $n$  of the sample.
- The overall size  $n$  of the sample can be obtained by adding the numbers of elements in each sub-sample:  $n = n_1 + \dots + n_m$ .

## 7. Good news: standard deviation is decomposable (cont-d)

- The sum of all  $x_i$ 's can be obtained by adding the sums corresponding to all sub-samples: 
$$\sum_{i=1}^n x_i = \sum_{j=1}^m \sum_{i \in N_j} x_i.$$
- Each such sub-sample sum is equal to  $n_j \cdot \bar{x}_j$ .
- Thus, we have 
$$\sum_{i=1}^n x_i = \sum_{j=1}^m n_j \cdot \bar{x}_j.$$
- So, 
$$\bar{x} = \frac{n_1 \cdot \bar{x}_1 + \dots + n_m \cdot \bar{x}_m}{n_1 + \dots + n_m}.$$
- Similarly:
  - if for each sub-sample, we know the number of elements, the mean, and the variance over each sub-sample,
  - then we can reconstruct the overall number of elements, mean, and the variance.

## 8. Good news: standard deviation is decomposable (cont-d)

- Indeed, it is known that the variance can be represented in the equivalent form  $V = M - (\bar{x})^2$ , where  $M$  denotes the second sample moment

$$M \stackrel{\text{def}}{=} \sum_{i=1}^n x_i^2.$$

- If we know the mean  $\bar{x}$  and the variance  $V$ , we can therefore reconstruct the second moment as  $M = V + (\bar{x})^2$ .
- Similarly, if we know the variance  $V_j$  and mean  $\bar{x}_j$  for each sub-sample, we can reconstruct each sub-sample second moment as

$$M_j = V_j + (\bar{x}_j)^2.$$

- Similarly to the case of the mean, we can reconstruct the overall second moment by using the following formula:

$$M = \frac{n_1 \cdot M_1 + \dots + n_m \cdot M_m}{n_1 + \dots + n_m}.$$

## 9. Good news: standard deviation is decomposable (cont-d)

- Then, we can reconstruct  $V$  as  $M - (\bar{x})^2$ .
- Because of the decomposability property, it is possible to easily process the census results as follows.
- For each town, we compute the three values – the number of people, the mean, and the variance – over this town.
- Then, for each state:
  - we take the three values corresponding to each town from this state, and
  - we combine them into the three values corresponding to the state.
- Finally:
  - we take the three values corresponding to each state, and
  - we combine them into the desired three values describing the overall census results.

## 10. Limitations of variance

- The problem with variance – or, equivalently, with coefficient of variation – is that it places too much weight on huge differences  $x_i - \bar{x}$ .
- For example, for incomes, it provides a good understanding of how many billionaires and multi-millionaires we have.
- However, their contribution hides an important information of how equal (or how unequal) are the incomes of the vast majority of people.
- It is therefore desirable to come up with decomposable measures that are less dependent on the some outliers.

## 11. Theil index: original forms

- Computation of the coefficient of variation is based on computing the sample mean and the value  $I \stackrel{\text{def}}{=} \frac{1}{n} \cdot \sum_{i=1}^n f(r_i)$ .
- For  $CV$ , we use a smooth function  $f(r) = (r - 1)^2$ .
- A natural idea is to use the same formula, but with some other smooth – e.g., twice differentiable – function  $f(r)$ .
- In the 1960s, a Dutch econometrician Henri Theil noticed that:
  - if we choose  $f(r) = \ln(r)$  or  $f(r) = r \cdot \ln(r)$ ,
  - then we still get decomposable indices.

## 12. Theil index: original forms (cont-d)

- Namely, if we know the number of elements  $n_j$ , the mean  $\bar{x}_j$ , and the value  $I_j$  of the index for each sub-sample, then:
  - based on this information,
  - we can uniquely reconstruct the number of elements  $n$ , the mean  $\bar{x}$ , and the index  $I$  corresponding the whole sample.
- Similar formulas:
  - with a properly defined individual discrimination instead of the income,
  - have been successfully used to detect (and debug) fairness defects in socioeconomic applications of deep neural networks.

### 13. Other decomposable versions of the Theil index

- Other decomposable versions of the Theil index were found: they correspond to  $f(r) = r^\alpha - 1$  for any  $\alpha$ .
- A natural question is: to provide a complete description of all smooth functions  $f(r)$  for which the index  $I$  is decomposable.
- A partial answer to this question was given in 1980 – under an additional condition that:
  - the formula describing of the index of the sample in terms of indices of sub-samples
  - is linear.
- It turns out that:
  - under this assumption,
  - the already proposed functions  $\ln(r)$ ,  $r \cdot \ln(r)$ , and  $r^\alpha$  are the only ones for which the corresponding index is decomposable.

## 14. Other decomposable versions of the Theil index (cont-d)

- The remaining question is: what will happen in the general case, when we do not make this linearity assumption?
- In this talk:
  - we provide a complete description of functions  $f(r)$  for which the index  $I$  is decomposable,
  - without making an additional assumption that decomposability is described by a linear formula.
- It turns out that even without this assumption, no other cases of decomposability appear.

## 15. Other decomposable versions of the Theil index (cont-d)

- In other words, the already proposed functions  $\ln(r)$ ,  $r \cdot \ln(r)$ , and  $r^\alpha$  are the only ones for which the corresponding index is decomposable.
- To summarize:
  - it is known that these functions lead to a decomposable index;
  - we prove that, vice versa, if a function leads to a decomposable index, then this function is of one of the three above types;
  - thus, no other function leads to a decomposable index.

## 16. Main definition

- We say that a twice differentiable function  $f(r)$  is *decomposable* if: the following property holds:
  - for each tuple  $x_1, \dots, x_n$  of positive real numbers, and
  - for each subdivision of the set  $N = \{1, \dots, n\}$  into disjoint subsets  $N = N_1 \cup \dots \cup N_m$ .
- If for each subset  $j$ , we know the number of elements  $n_j$  in this subset,
  - the mean  $\bar{x}_j$  over this subset, and
  - the corresponding value  $I_j$  of the index  $I$ : 
$$I_j = \frac{1}{n_j} \cdot \sum_{i \in N_j} f\left(\frac{x_i}{\bar{x}_j}\right),$$
- then, based on this information, we can uniquely reconstruct:
  - the overall number of elements  $n$ , the overall mean  $\bar{x}$ , and
  - the overall value  $I$  of the index  $I$ : 
$$I = \frac{1}{n} \cdot \sum_{i=1}^n f\left(\frac{x_i}{\bar{x}}\right).$$

## 17. Main result

- Our main result is to describe all decomposable functions.
- To formulate our result, we need the following auxiliary definition.
- We say that two functions  $f(r)$  and  $g(r)$  are *equivalent* if there exist real numbers  $a \neq 0$ ,  $b$  and  $c$  for which, for all  $r$ , we have

$$g(r) = a \cdot f(r) + b \cdot x + c.$$

- If two functions are equivalent, then the corresponding indices  $I(g)$  and  $I(f)$  are related as follows:

$$I(g) = \frac{1}{n} \cdot \sum_{i=1}^n g(r_i) = a \cdot \frac{1}{n} \cdot \sum_{i=1}^n f(r_i) + b \cdot \sum_{i=1}^n r_i + c \cdot \sum_{i=1}^n 1.$$

- Here, we denoted  $r_i \stackrel{\text{def}}{=} \frac{x_i}{x}$ .

## 18. Main result (cont-d)

- Here,  $\sum_{i=1}^n 1 = n$  and

$$\sum_{i=1}^n r_i = \sum_{i=1}^n \frac{x_i}{\bar{x}} = \frac{1}{\bar{x}} \cdot \sum_{i=1}^n x_i = \frac{x_1 + \dots + x_n}{\frac{x_1 + \dots + x_n}{n}} = n.$$

- Thus,  $I_g = a \cdot I_f + b \cdot n + c \cdot n$ .
- So, if we know  $I_f$ , we can uniquely reconstruct  $I_g$ , and vice versa.
- In this sense, the indices corresponding to functions  $f(r)$  and  $g(r)$  are indeed equivalent.
- Now, we are ready to formulate our main result.
- *A function  $f(r)$  is decomposable if and only if it is equivalent to one of the following functions:  $\ln(r)$ ,  $r \cdot \ln(r)$ , and  $r^\alpha$  for some  $\alpha$ .*

## 19. Proof

- It is known that functions from all the three types are decomposable.
- So, to complete our proof, we need to prove that:
  - if a function  $f(r)$  is decomposable,
  - then it is indeed equivalent to one of the functions listed in the formulation of our theorem.
- If a subset  $N_j$  consists of a single element  $x$ , then:
  - its number of elements is  $n_j = 1$ ,
  - its mean is  $\bar{x}_j = x$ ,
  - and – since here  $x_i = \bar{x}$  – its index  $I$  is equal to  $f(1)$ .
- Let us pick some natural number  $n \geq 4$ .
- Let us consider a tuple  $(x_1, \dots, x_n, x)$  consisting of  $n + 1$  positive numbers for which the sum of the first  $n$  elements is equal to  $n$ .

## 20. Proof (cont-d)

- For this tuple, the mean value is equal to

$$\bar{x} = \frac{x_1 + \dots + x_n + x}{n + 1} = \frac{n + x}{n + 1}.$$

- Let us denote  $\lambda \stackrel{\text{def}}{=} \frac{1}{\bar{x}} = \frac{n + 1}{n + x}$ .

- Then, by definition of  $\lambda$ , we have  $r_i = \lambda \cdot x_i$  and thus, the index  $I$  is equal to  $I = \frac{1}{n + 1} \cdot \left( \sum_{i=1}^n f(\lambda \cdot x_i) + f(\lambda \cdot x) \right)$ .

- Let us consider a subdivision of this tuple into two subsets:  $N_1 = \{1, \dots, n\}$  and  $N_2 = \{n + 1\}$ .

- For the subset  $N_1$ , the mean  $\bar{x}_1$  is equal to 1, so we have  $r_i = x_i$  and thus, the index  $I$  is described by the formula  $I_1 = \frac{1}{n} \cdot \sum_{i=1}^n f(x_i)$ .

- For the subset  $N_2$ , as we showed, the mean is  $\bar{x}_2 = x$  and the index is  $I_2 = f(1)$ .

## 21. Proof (cont-d)

- For this subdivision, decomposability means that:
  - the value  $I$  is uniquely determined
  - if we know  $I_1$  the sample size  $n$ , the mean  $\bar{x}_1$ , and the values  $\lambda$  and  $x$ .
- The value  $S_\lambda \stackrel{\text{def}}{=} \sum_{i=1}^n f(\lambda \cdot x_i)$  is equal to  $(n + 1) \cdot I - f(\lambda \cdot x)$ .
- Since  $x$  is uniquely determined by  $\lambda$ , we can conclude that the value  $S_\lambda$  is also uniquely determined by values  $\lambda$ ,  $I_1$ ,  $n$ , and  $\bar{x}_1$ .
- One can check that, once we know  $n$ , then knowing  $I_1$  is equivalent to knowing  $S_1 \stackrel{\text{def}}{=} \sum_{i=1}^n f(x_i)$ , since  $S_1$  is equal to  $n \cdot I_1$ .
- Similarly, once we know  $n$ , knowing  $\bar{x}_1$  is equivalent to knowing the sum  $x_1 + \dots + x_n = n \cdot \bar{x}_1$ .

## 22. Proof (cont-d)

- In other words, decomposability means that if for some other tuple  $y_1, \dots, y_n$ :
  - we have the same values of the sum  $S_1$  and of the sum of  $n$  elements  $y_i$ ,
  - we should have the same value of the quantity  $S_\lambda$ .
- So, the following property must be satisfied:

– if we have  $f(y_1) + \dots + f(y_n) = f(x_1) + \dots + f(x_n)$  and

$$y_1 + \dots + y_n = x_1 + \dots + x_n = n,$$

– then we should have

$$f(\lambda \cdot y_1) + \dots + f(\lambda \cdot y_n) = f(\lambda \cdot x_1) + \dots + f(\lambda \cdot x_n).$$

- This property must hold for any  $\lambda$  that can be obtained by the above formula.

## 23. Proof (cont-d)

- For every positive  $\lambda < 1 + 1/n$ , we can find an  $x > 0$  for which this formula holds: namely, we can take  $x = \frac{n+1}{\lambda} - n$ .
- Thus, the above property must be satisfied for all  $\lambda$  between 0 and  $1 + 1/n$ . Let us use this property to describe the function  $f(r)$ .
- Let us consider the values  $y_i$  that are close to  $x_i$ , i.e., for which, for some values  $d_i$ , we have  $y_i = x_i + s \cdot d_i$  for some small  $s$ .
- For such  $y_i$ , we have

$$f(y_i) = f(x_i + s \cdot d_i) = f(x_i) + f'(x_i) \cdot s \cdot d_i + o(s).$$

- Thus, the equality of the sums takes the form

$$f'(x_1) \cdot s \cdot d_1 + \dots + f'(x_n) \cdot s \cdot d_n + o(s) = 0.$$

- If we divide both sides by  $s$ , by get an equivalent equality

$$f'(x_1) \cdot d_1 + \dots + f'(x_n) \cdot d_n + o(1) = 0.$$

## 24. Proof (cont-d)

- Similarly, both given equalities take the form

$$d_1 + \dots + d_n + o(1) = 0, \text{ and}$$

$$f'(\lambda \cdot x_1) \cdot d_1 + \dots + f'(\lambda \cdot x_n) \cdot d_n + o(1) = 0.$$

- So, in the limit  $s \rightarrow 0$ , we conclude that for each vector  $d = (d_1, \dots, d_n)$ :

– if we have  $f'(x_1) \cdot d_1 + \dots + f'(x_n) \cdot d_n = 0$  and  $d_1 + \dots + d_n = 0$ ,

– then we should have  $f'(\lambda \cdot x_1) \cdot d_1 + \dots + f'(\lambda \cdot x_n) \cdot d_n = 0$ .

- Each of these expressions is a scalar (dot) product of the vector  $d$  with, correspondingly, vectors  $a \stackrel{\text{def}}{=} (f'(x_1), \dots, f'(x_n))$ ,  $e \stackrel{\text{def}}{=} (1, \dots, 1)$ , and

$$b \stackrel{\text{def}}{=} (f'(\lambda \cdot x_1), \dots, f'(\lambda \cdot x_n)).$$

- The scalar product of two vectors is 0 if and only if these two vectors are orthogonal.

## 25. Proof (cont-d)

- Thus, we conclude that every vector  $d$  which is orthogonal to both  $a$  and  $e$  is also orthogonal to  $b$ .
- This means that the vector  $b$  must belong to the plane generated by  $a$  and  $e$ .
- Otherwise, we can decompose  $b$  it into:
  - its projection  $\text{pr}_{a,e}(b)$  to this plane and
  - the remainder  $R = b - \text{pr}_{a,e}(b)$  which is orthogonal to this plane.
- This remainder is orthogonal to  $a$  and  $e$  but not to  $b$  – which would contradict to the property described earlier.
- The fact that  $b$  belongs to the plane generated by the vector  $a$  and  $e$  means that, for some real numbers  $A$  and  $B$ , we have  $b = A \cdot a + B \cdot e$ .
- In terms of vector components, this means that

$$f'(\lambda \cdot x_i) = A \cdot f'(x_i) + B$$

## 26. Proof (cont-d)

- In general, the coefficient  $A$  and  $B$  depend on  $\lambda$  and on the initial tuple  $(x_1, \dots, x_n)$ .
- So, strictly speaking, we should write

$$f'(\lambda \cdot x_i) = A(\lambda, x_1, \dots, x_n) \cdot f'(x_i) + B(\lambda, x_1, \dots, x_n).$$

- Let us show that  $A$  and  $B$  do not depend on  $x_1$ .
- Indeed, for  $i = 2$  and  $i = 3$ , we get

$$f'(\lambda \cdot x_2) = A(\lambda, x_1, \dots, x_n) \cdot f'(x_2) + B(\lambda, x_1, \dots, x_n);$$

$$f'(\lambda \cdot x_3) = A(\lambda, x_1, \dots, x_n) \cdot f'(x_3) + B(\lambda, x_1, \dots, x_n).$$

- Let us subtract the second equation from the first one and divide both sides of the resulting equation by the coefficient at  $A(\lambda, x_1, \dots, x_n)$ .
- Then, we conclude that

$$A(\lambda, x_1, \dots, x_n) = \frac{f'(\lambda \cdot x_2) - f'(\lambda \cdot x_3)}{f'(x_2) - f'(x_3)}.$$

## 27. Proof (cont-d)

- So:
  - unless the derivative is a constant – and thus, the function  $f(x)$  is linear,
  - the right-hand side depends only on  $\lambda$ ,  $x_2$ , and  $x_3$  (and does not depend on  $x_1$ ).

- Thus, the left-hand side – i.e., the value  $A(\lambda, x_1, \dots, x_n)$  – should also only depend on  $x_2$  and  $x_3$ .

- So, we will write  $A(\lambda, x_1, \dots, x_n) = A(\lambda, x_2, x_3)$ .

- From the equality describing  $f'(\lambda \cdot x_3)$ , we can now conclude that

$$B(\lambda, x_1, \dots, x_n) = f'(\lambda \cdot x_2) - A(\lambda, x_2, x_3) \cdot f'(x_2).$$

- Here too, the right-hand side does not depend on  $x_1$ .
- So the left-hand side – which is  $B(\lambda, x_1, \dots, x_n)$  – also should not depend on  $x_1$ .

## 28. Proof (cont-d)

- Thus, indeed, neither  $A$  nor  $B$  depend on  $x_1$ .
- Similarly, we can conclude that  $A$  and  $B$  cannot depend on  $x_2$ , on  $x_3$ , etc.
- So  $A$  and  $B$  only depend on  $\lambda$ :

$$F(\lambda \cdot r) = A(\lambda) \cdot F(r) + B(\lambda).$$

- Here, we denoted  $F(r) \stackrel{\text{def}}{=} f'(r)$ .
- The formulas for  $A$  and  $B$  take the form

$$A(\lambda) = \frac{f'(\lambda \cdot x_2) - f'(\lambda \cdot x_3)}{f'(x_2) - f'(x_3)} \text{ and } B(\lambda) = f'(\lambda \cdot x_2) - A(\lambda) \cdot f'(x_2).$$

- We assumed that the function  $f(r)$  is twice differentiable.
- Thus, its derivative  $F(r) = f'(r)$  is differentiable.
- So, due to the above formulas for  $A$  and  $B$ , the functions  $A(\lambda)$  and  $B(\lambda)$  are differentiable too.

## 29. Proof (cont-d)

- So, we can differentiate both sides of the formula for  $F(\lambda \cdot r)$  by  $\lambda$ , and get  $x \cdot F'(\lambda \cdot r) = A'(\lambda) \cdot F(r) + B'(\lambda)$ .
- In particular, for  $\lambda = 1$ , we get  $r \cdot \frac{dF}{dr} = a_0 \cdot F + b_0$ .
- Here we denoted  $a_0 \stackrel{\text{def}}{=} A'(1)$  and  $b_0 \stackrel{\text{def}}{=} B'(1)$ .
- We can separate the variables if we multiply both sides by  $dr$  and divide both sides by  $r$  and  $a_0 \cdot F + b_0$ .
- Then, we get  $\frac{dF}{a_0 \cdot F + b_0} = \frac{dr}{r}$ .
- If  $a_0 = 0$ , then, integrating both sides, we get  $b_0^{-1} \cdot F = \ln(r) + C$ , where  $C$  is an integration constant, i.e.,  $F(x) = f'(r) = b_0 \cdot \ln(r) + b_0 \cdot C$ .
- Integrating again, we conclude that  $f(r) = b_0 \cdot r \cdot \ln(r) + \text{const} \cdot x + \text{const}$ , i.e., that  $f(r)$  is equivalent to  $r \cdot \ln(r)$ .
- If  $a_0 \neq 0$ , then for  $G \stackrel{\text{def}}{=} F + b_0/a_0$ , we get  $\frac{dG}{a_0 \cdot G} = \frac{dr}{r}$ .

### 30. Proof (cont-d)

- Integrating both sides, we get  $a_0^{-1} \cdot \ln(G) = \ln(r) + C$ , so  $\ln(G) = a_0 \cdot \ln(r) + a_0 \cdot C$ .
- Applying  $\exp(x)$  to both sides, we conclude that  $G(r) = \text{const} \cdot r^{a_0}$ .
- Thus  $F(r) = G(r) - b_0/a_0$  has the form

$$f'(r) = F(r) = \text{const} \cdot r^{a_0} + \text{const}.$$

- To get  $f(r)$ , we need to integrate one more time.
- When  $a_0 = -1$ , we get  $f(r) = \text{const} \cdot \ln(r) + \text{const} \cdot r + \text{const}$ , i.e., we get a function equivalent to  $\ln(r)$ .
- When  $a_0 \neq -1$ , we get  $f(r) = \text{const} \cdot r^{a_0+1} + \text{const} \cdot x + \text{const}$ , i.e., we get a function equivalent to  $r^\alpha$  for  $\alpha = a_0 + 1$ .
- The theorem is proven.

## 31. Acknowledgments

This work was supported in part by:

- National Science Foundation grants 1623190, HRD-1834620, HRD-2034030, and EAR-2225395;
- AT&T Fellowship in Information Technology;
- program of the development of the Scientific-Educational Mathematical Center of Volga Federal District No. 075-02-2020-1478, and
- a grant from the Hungarian National Research, Development and Innovation Office (NRDI).