# How to Estimate Individual Contributions to a Group Project 

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#### Abstract

In many real-life situation, the only information that we have for estimating the individual contributions $E_{j}$ to a group project consists of individual estimates $e_{i j}$ of contributions of other participants $j$. In this paper, we describe a new faster algorithm for estimating individual contributions to a group project based on the estimates $e_{i j}$. (C) 2010 World Academic Press, UK. All rights reserved.


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## 1 Formulation of the Problem

Formulation of the practical problem. How can we estimate individual contributions to a group project? This problem is important in education when several students work together on a project, it is important in the business environment when several people work together on a joint project.

In all such situations, we need to know the relative contributions $E_{1}, \ldots, E_{n}$ of all $n$ participants, relative in the sense that they represent the fraction of the overall credit - and thus, the sum of these contributions should be equal to 1 :

$$
\begin{equation*}
\sum_{i=1}^{n} E_{i}=1 \tag{1}
\end{equation*}
$$

Available information for solving the problem. In many practical situation, the only available information for estimating contributions consists of the estimates that different participants give to each other's contribution. In this case, we have $n^{2}$ values $e_{i j}(1 \leq i, j \leq n)$ - estimates made by the $i$-th participate of the contribution of the $j$-th participant.

Ideal case when all estimates are unbiased. In the ideal case when all estimates are unbiased, for each participant $j$, we have $n$ estimates $e_{1 j}, \ldots, e_{n j}$ for the desired value $E_{j}$. In this case, we have $n$ approximate equalities to find $E_{j}$ :

$$
\begin{equation*}
E_{j} \approx e_{1 j}, \quad \ldots, \quad E_{j} \approx e_{n j} \tag{2}
\end{equation*}
$$

To find a reasonable estimate $E_{j}$ from these approximate equalities, a natural idea is to use the Least Squares technique and find the value $E_{j}$ for which the sum

$$
\begin{equation*}
\sum_{i=1}^{n}\left(E_{j}-e_{i j}\right)^{2} \tag{3}
\end{equation*}
$$

is the smallest possible. This is a textbook use of the Least Squares method, to combine several estimates of the same quantity, and the solution to this optimization problem is well known - it is the arithmetic average of these estimates:

$$
\begin{equation*}
E_{j}=\frac{e_{1 j}+\ldots+e_{n j}}{n} \tag{4}
\end{equation*}
$$

[^0]Problem: self-estimates are biased. In practice, estimates of others' contributions are often unbiased, but it is very difficult to get an unbiased estimate of one's own contribution in comparison with the contributions of others.

In other words, while the estimates $e_{i j}$ for $i \neq j$ are really unbiased, the estimates $e_{i i}$ are too subjective and biased to be useful.

Available information for solving the problem: revisited. Because of the bias, we can say that the only available information about each value $E_{j}$ consists of estimates $e_{i j}$ with $i \neq j$.

What was known before. The problem of estimating the values $E_{j}$ based on the estimates $e_{i j}$ with $i \neq j$ was considered earlier; see, e.g., [1, 2] and references therein. In particular, [2] describes an algorithm for estimating $E_{j}$.

Limitations of the previous approaches. The algorithm from [2] is based on solving a highly non-linear optimization problem and is, therefore, reasonably time-consuming.

What we do in this paper. In this paper, we use ideas from [1] to come up with a much faster algorithm for estimating $E_{j}$, an algorithm whose most time-consuming step is solving a system of linear equations.

## 2 Towards the Formulation of the Problem in Precise Terms

In principle, each participant $i$ provides relative estimates $e_{i 1}, \ldots, e_{i n}$ which add up to 1 . Once we have absolute estimates $a_{i 1}, \ldots, a_{i n}$, we get the relative contributions $e_{i j}$ by dividing each value $a_{i j}$ by the total contribution $a_{i 1}+\ldots+a_{i n}$ :

$$
\begin{equation*}
e_{i j}=\frac{a_{i j}}{a_{i 1}+\ldots+a_{i n}} \tag{5}
\end{equation*}
$$

If all these estimates were unbiased, then each estimate $e_{i j}$ would provide an unbiased estimate of $E_{j}$.
In particular, in the idealized case when all estimates are exact, we have $a_{i j}=c_{i} \cdot E_{j}$ for some value $c_{i}$. Thus, for the normalized values, we get

$$
\begin{equation*}
e_{i j}=\frac{c_{i} \cdot E_{j}}{c_{i} \cdot E_{1}+\ldots+c_{i} \cdot E_{n}}=\frac{E_{j}}{E_{1}+\ldots+E_{n}} \tag{6}
\end{equation*}
$$

hence $e_{i j}=E_{j}$ and

$$
\begin{equation*}
e_{i 1}+\ldots+e_{i n}=E_{1}+\ldots+E_{n}=1 \tag{7}
\end{equation*}
$$

In practice, as we have mentioned, each self-estimate $a_{i i}$ is biased: $a_{i i} \neq c_{i} \cdot E_{i}$. As a result, even when the $i$-th participant provides the exact absolute values of the contributions $c_{i} \cdot E_{j}$ for $i \neq j$, the corresponding relative (normalized) contribution

$$
\begin{gather*}
e_{i j}=\frac{a_{i j}}{a_{i 1}+\ldots+a_{i n}}= \\
\frac{c_{i} \cdot E_{j}}{c_{i} \cdot E_{1}+\ldots+c_{i} \cdot E_{i-1}+a_{i i}+c_{i} \cdot E_{i+1}+\ldots+c_{i} \cdot E_{n}}=\frac{E_{j}}{s_{i}} \tag{8}
\end{gather*}
$$

(where

$$
\begin{equation*}
\left.s_{i}=E_{1}+\ldots+E_{i-1}+\frac{a_{i i}}{c_{i}}+E_{i+1}+\ldots+E_{n},\right) \tag{9}
\end{equation*}
$$

is different from $E_{j}$ : instead of the correct value

$$
\begin{equation*}
E_{j}=\frac{E_{j}}{E_{1}+\ldots+E_{i-1}+E_{i}+E_{i+1}+\ldots+E_{n}}=\frac{E_{j}}{1} \tag{10}
\end{equation*}
$$

we get the new value

$$
\begin{equation*}
e_{i j}=\frac{E_{j}}{s_{i}} \tag{11}
\end{equation*}
$$

where, due to $a_{i i} \neq c_{i} \cdot E_{i}$, we have

$$
\begin{equation*}
s_{i} \stackrel{\text { def }}{=} E_{1}+\ldots+E_{i-1}+\frac{a_{i i}}{c_{i}}+E_{i+1}+\ldots+E_{n} \neq 1 \tag{12}
\end{equation*}
$$

Thus, the relative estimates $e_{i j}$ of $j$-th contribution will be equal not to $E_{j}$, but to the normalized value (11). Since the estimates are only approximate, we have an approximate equality

$$
\begin{equation*}
e_{i j} \approx \frac{E_{j}}{s_{i}} \tag{13}
\end{equation*}
$$

or, equivalently,

$$
\begin{equation*}
E_{j} \approx e_{i j} \cdot s_{i} \tag{14}
\end{equation*}
$$

Here, the values $e_{i j}$ are known, while the estimates $E_{j}$ and the values $s_{i}$ are unknown. The Least Squares approach now means that we minimize the sum of the squares of the discrepancies

$$
\begin{equation*}
\sum_{i \neq j}\left(E_{j}-e_{i j} \cdot s_{i}\right)^{2} \tag{15}
\end{equation*}
$$

under the constraint (1). Thus, we arrive at the following problem.
Precise formulation of the problem. Minimize the expression 15 under the constraint (1).

## 3 Solving the Problem

Towards solving the problem. First, let us use the Lagrange multiplier method to reduce the above constrained optimization problem to the following un-constrained one: minimize

$$
\begin{equation*}
J \stackrel{\text { def }}{=} \sum_{i \neq j}\left(E_{j}-e_{i j} \cdot s_{i}\right)^{2}+\lambda \cdot\left(\sum_{i=1}^{n} E_{i}-1\right) \tag{16}
\end{equation*}
$$

where the Lagrange multiplier $\lambda$ must be chosen in such a way that the constraint (1) is satisfied.
Since the function $J$ attains minimum, its partial derivatives must be equal to 0 . Differentiating $J$ with respect to $E_{j}$ and equating the derivative to 0 , we conclude that

$$
\begin{equation*}
\frac{\partial J}{\partial E_{j}}=2 \sum_{i \neq j}\left(E_{j}-e_{i j} \cdot s_{i}\right)+\lambda=0 \tag{17}
\end{equation*}
$$

Dividing both sides of this equality by 2 and taking into account that $E_{j}$ is repeated for each $i \neq j$, i.e., $n-1$ times, we conclude that

$$
\begin{equation*}
(n-1) \cdot E_{j}-\sum_{i \neq j} e_{i j} \cdot s_{i}=-\frac{\lambda}{2} \tag{18}
\end{equation*}
$$

This equation can be somewhat simplified if we take $e_{i i} \stackrel{\text { def }}{=} 0$; then, the sum over all $i \neq j$ can be simply described as the sum over all $i$ :

$$
\begin{equation*}
(n-1) \cdot E_{j}-\sum_{i=1}^{n} e_{i j} \cdot s_{i}=-\frac{\lambda}{2} \tag{19}
\end{equation*}
$$

It should be mentioned that the values $e_{i i}=0$ are selected only for the purpose of simplifying computations; these values do not mean that we somehow think that each participate estimates his or new own contribution as 0 .

Differentiating $J$ with respect to $s_{i}$ and equating the derivative to 0 , we conclude that

$$
\begin{equation*}
\frac{\partial J}{\partial s_{i}}=2 \sum_{j \neq i}\left(E_{j}-e_{i j} \cdot s_{i}\right) \cdot e_{i j}=0 \tag{20}
\end{equation*}
$$

Dividing both sides of this equality by 2 , we get

$$
\begin{equation*}
s_{i} \cdot \sum_{j \neq i} e_{i j}^{2}=\sum_{j \neq i} E_{j} \cdot e_{i j} \tag{21}
\end{equation*}
$$

or, equivalently, that

$$
\begin{equation*}
s_{i}=\frac{\sum_{\ell \neq i} E_{\ell} \cdot e_{i \ell}}{\sum_{m \neq i} e_{i m}^{2}} . \tag{22}
\end{equation*}
$$

(Here, for convenience of the following transformations, we renamed the indices in the two sums into two different ones.) By taking $e_{i i}=0$, we can simplify this expression into the following one:

$$
\begin{equation*}
s_{i}=\frac{\sum_{\ell=1}^{n} E_{\ell} \cdot e_{i \ell}}{\sum_{m=1}^{n} e_{i m}^{2}} \tag{23}
\end{equation*}
$$

Substituting the expression (23) into the formula (19), we conclude that

$$
\begin{equation*}
(n-1) \cdot E_{j}-\sum_{i=1}^{n} e_{i j} \cdot \frac{\sum_{\ell=1}^{n} E_{\ell} \cdot e_{i \ell}}{\sum_{m=1}^{n} e_{i m}^{2}}=-\frac{\lambda}{2} \tag{24}
\end{equation*}
$$

i.e.,

$$
\begin{equation*}
(n-1) \cdot E_{j}-\sum_{\ell=1}^{n} c_{j, \ell} \cdot E_{\ell}=-\frac{\lambda}{2} \tag{25}
\end{equation*}
$$

where

$$
\begin{equation*}
c_{j, \ell} \stackrel{\text { def }}{=} \sum_{i=1}^{n} \frac{e_{i j} \cdot e_{i \ell}}{c_{i}}, \tag{26}
\end{equation*}
$$

where

$$
\begin{equation*}
c_{i} \stackrel{\text { def }}{=} \sum_{m=1}^{n} e_{i m}^{2} \tag{27}
\end{equation*}
$$

The values $c_{j, \ell}$ can be explicitly computed from the known values $e_{i j}$. To solve the resulting system of linear equations 25 with the unknown value $\lambda$, it is sufficient to solve it for $\lambda=-2$, when $-\frac{\lambda}{2}=1$, and then multiply the resulting values $e_{j}$ by a common factor in such a way that the new values add up to 1 : i.e., take

$$
\begin{equation*}
E_{j}=\frac{e_{j}}{S} \tag{28}
\end{equation*}
$$

where

$$
\begin{equation*}
S \stackrel{\text { def }}{=} \sum_{i=1}^{n} e_{i} \tag{29}
\end{equation*}
$$

Thus, we arrive at the following algorithm.
New algorithm for solving the problem. Given the values $e_{i j}$ for $i \neq j$, we first take $e_{i i} \stackrel{\text { def }}{=} 0$. Then, we compute the values

$$
\begin{equation*}
c_{i} \stackrel{\text { def }}{=} \sum_{m=1}^{n} e_{i m}^{2} \tag{30}
\end{equation*}
$$

and

$$
\begin{equation*}
c_{j, \ell} \stackrel{\text { def }}{=} \sum_{i=1}^{n} \frac{e_{i j} \cdot e_{i \ell}}{c_{i}}, \tag{31}
\end{equation*}
$$

and solve the following system of linear equations

$$
\begin{equation*}
(n-1) \cdot e_{j}-\sum_{\ell=1}^{n} c_{j, \ell} \cdot e_{\ell}=1 \tag{32}
\end{equation*}
$$

After this, we compute the sum

$$
\begin{equation*}
S=\sum_{i=1}^{n} e_{i} \tag{33}
\end{equation*}
$$

and then, the desired estimates as

$$
\begin{equation*}
E_{j}=\frac{e_{j}}{S} \tag{34}
\end{equation*}
$$

Discussion. In this algorithm, the most time-consuming step is solving a system of linear equations. Thus, this algorithm is indeed much faster than the algorithm from [2] that requires a solution of the non-linear optimization problem.

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## References

[1] Kreinovich, V., How to Pay for Collective Creative Activity?, Technical Report, Informatika Research Center, St. Petersburg, Russia, 1989.
[2] Leung, Y.-W., Least-squar-error estimate of individual contribution in group project, IEEE Transactions on Education, vol.41, no.4, pp.282-284, 1998.


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