## The Official Original Derivation of AQWV

This is the definitive official derivation of AQWV, which is really a modified version of ATWV.
Note that there are three main "input" weights: $C, V$, and an overall $a$-priori estimate for $P_{\text {Relevant }}$ The input weights do not directly include a cost for a miss.

Note well that there are two different kinds of $P_{\text {Relevant }}$ in this document.

- The first in an a-priori estimate for $P_{\text {Relevant }}$ across all the queries and all the datasets. This estimate enters into the factor called $\beta$ (but not into the calculation of $P_{\text {miss }}$ and $P_{f a}$ for a specific system on a specific query on a specific dataset).
- The second is the actual $P_{\text {Relevant }}$ for a specific system for a specific query on a specific dataset. This actual statistic enters into the calculation of $P_{\text {miss }}$ and $P_{f a}$ (but not into the calculation of the factor called $\beta$ ).
This distinction will be clear by the end of the derivation of Value, below.


## The input weights:

$C$ is the cost of an incorrect or spurious detection (a false alarm)
(that is, returning a document that is not relevant)
$V$ is the value of a correct detection
(that is, correctly returning a document that is actually relevant)
The value of $P_{\text {Relevant }}$ incorporated into $\beta$ is an a-priori estimate of $P_{\text {Relevant }}$ across all the datasets, and is held constant acrosss the entire evaluations.

## The variables in the formulas:

$N_{f a}$ is the number of false alarms
(documents retrieved that are not relevant)
$N_{\text {correct }}$ is the number of correctly retrieved documents
(documents retrieved that are relevant)
$N_{\text {miss }}$ is the number of relevant documents that were not retrieved
$N_{\text {total }}$ is the total number of documents in the dataset
$N_{\text {relevant }}$ is the number of relevant documents in the dataset
$N_{\text {nonRelevant }}$ is the number of non-relevant documents in the dataset
Note that (Ntrue+NnonTarg) = Ntotal
$P_{\text {relevant }}=\left(N_{\text {relevant }} / N_{\text {total }}\right)$
$1 / P_{\text {relevant }}=\left(N_{\text {total }} / N_{\text {relevant }}\right)$
We will use that formulation of $1 / P_{\text {relevant }}$ in our derivation of Value, below.

$$
\begin{aligned}
& \text { Value }=\left[\left(V * N_{\text {correct }}\right) \quad-\left(C * N_{f a}\right)\right] /\left(V * N_{\text {relevant }}\right) \quad<==\text { This is the original idea } \\
& =\frac{V * N_{\text {correct }}}{V * N_{\text {relevant }}} \quad-\quad \frac{(C / V) * N_{\text {fa }}}{V * N_{\text {relevant }}} \\
& =\left(\frac{N_{\text {correct }}}{N_{\text {relevant }}}\right) \quad-\quad \frac{(C / V) * N_{\text {fa }}}{N_{\text {relevant }}} \\
& =\left(\frac{N_{\text {relevant }}-N_{\text {miss }}}{N_{\text {relevant }}}\right)-\quad \frac{(C / V) * N_{\text {fa }}}{N_{\text {relevant }}} \\
& =\left(\frac{N_{\text {relevant }}-N_{\text {miss }}}{N_{\text {relevant }}}\right)-\left[\frac{(C / V) * N_{f a}}{1} \quad * \quad \frac{1}{N_{\text {relevant }}}\right] \\
& =\left(\frac{N_{\text {relevant }}-N_{\text {miss }}}{N_{\text {relevant }}}\right)-\left[(C / V) * \quad \frac{N_{f a}}{1} \quad * \quad \frac{1}{N_{\text {relevant }}}\right] \\
& =\frac{N_{\text {relevant }}-N_{\text {miss }}}{N_{\text {relevant }}}-\left[(C / V) *\left(\frac{N_{\text {fa }}}{N_{\text {total }}-N_{\text {relevant }}}\right) *\left(\frac{N_{\text {total }}-N_{\text {relevant }}}{N_{\text {relevant }}}\right)\right] \\
& =P_{\text {correct }}-\left[(C / V) * \quad P_{f a} \quad *\left(\left(N_{\text {total }}-N_{\text {relevant }}\right) / N_{\text {relevant }}\right)\right] \\
& =1-P_{\text {miss }}-\left[(C / V) * \quad P_{f a} \quad *\left(N_{\text {nonRelevant }} / N_{\text {relevant }}\right)\right] \\
& =1-P_{\text {miss }}-\left[(C / V) *\left(N_{\text {nonRelevant }} / N_{\text {relevant }}\right) \quad * P_{f a}\right] \\
& =1-P_{\text {miss }}-\left[(C / V) *\left(\frac{N_{\text {nonRelevant }}}{N_{\text {relevant }}}+\frac{N_{\text {relevant }}}{N_{\text {relevant }}}-\frac{N_{\text {relevant }}}{N_{\text {relevant }}}\right) * P_{f a}\right] \\
& =1-P_{\text {miss }}-\left[(C / V) *\left(\frac{N_{\text {nonRelevant }}+N_{\text {relevant }}}{N_{\text {relevant }}}-\frac{N_{\text {relevant }}}{N_{\text {relevant }}}\right) * P_{f a}\right] \\
& =1-P_{\text {miss }} \\
& =1-P_{\text {miss }}-\left[(C / V) *\left(1 / P_{\text {relevant }} \quad-1\right) \quad * P_{f a}\right]
\end{aligned}
$$

If we let $\beta$ denote $(C / V) *\left(1 / P_{\text {relevant }}-1\right)$, then we can rewrite the above as Value $=1-P_{\text {miss }}-\beta * P_{f a}$ or as Value $=1-\left(P_{\text {miss }}+\beta * P_{f a}\right)$
However, note well, the value of $P_{\text {relevant }}$ that we actually incorporate into $\beta$ is not the value computed above. For $\beta$, we instead substitute our best $a$-priori estimate across our datasets, queries, and languages: we hold that estimate (and $\beta$ ) constant across entire evaluations so that we can make comparisons between systems and track progress from year to year. This allows apples-to-apples comparisons.

Value is for a particular query. The mean of Value over all the queries is $Q W V$ (Query Weighted Value). $A Q W V$ (Actual Query Weighted Value) is $Q W V$ when the system is run at its actual decision threshold (we call that threshold $\theta$ ).

