# Using a $\beta$-Contact Predictor to Guide Pairwise Sequence Alignments for Comparative Modeling Supplementary Material 

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## 1 Defining the Cost Function in Detail

Given a pairwise sequence alignment, $A$, between a template and a target sequence (the structure of the template being known), we define the cost, $c\left(A, S_{\text {tpl }}\right)$, as the sum of three contributions:

$$
\begin{equation*}
c\left(A, S_{t p l}\right)=c_{n w}(A)+c_{\beta i}\left(A, S_{t p l}\right)+c_{b c}\left(A, S_{t p l}\right) \tag{1}
\end{equation*}
$$

where $S_{t p l}$ is the structure of the template sequence.
The component $c_{n w}$ is the result of a classical similarity-based scoring scheme with affine gap penalties:

$$
\begin{equation*}
c_{n w}(A)=c_{g o} \cdot n_{g o}+c_{g x} \cdot n_{g x}+\sum_{i, j} M_{c}\left(P_{t p l_{i}}, P_{t g t_{j}}\right) \tag{2}
\end{equation*}
$$

where $i$ and $j$ indicate the position of the substituted residues, $n_{g o}$ the number of gap openings, and $n_{g x}$ the number of gap extensions, all according to the alignment A. $c_{g o}$ is the cost of opening of a new gap, $c_{g x}$ is the cost of extending a gap, and $M_{c}$ is a substitution cost matrix obtained by reversing a similarity scoring matrix $M_{s}$ (such as BLOSUM62):

$$
\begin{equation*}
M_{c}=-\left(M_{s}-\max \left(M_{s}\right)\right) \tag{3}
\end{equation*}
$$

The second term, $c_{\beta i}$, in Equation 1 is an additional gap penalty to penalize gaps within the $\beta$-strands of the template:

$$
\begin{equation*}
c_{\beta i}=n_{g \beta} \cdot c_{g \beta} \tag{4}
\end{equation*}
$$

where $c_{g \beta}$ is $\beta$-specific gap penalty and $n_{g \beta}$ is the number of gaps within $\beta$-strands.
The last term in Equation 1, $c_{b c}$, results from the evaluation of $\beta$-pairs in the target sequence (assigned from the template, based on the alignment). Considering $\tilde{p}\left(b p_{t g t}\right)$ as the estimation of the probability of the $\beta$-pair $b p_{t g t}$ being formed, it is reasonable that the cost $c\left(b p_{t g t}\right)$ should be proportional to $-\tilde{p}\left(b p_{t g t}\right)$. The value of the cost should be large enough to allow the overall cost function to escape from misleading minima obtained with the standard scoring system. Thus, the cost should also be proportional to the number of residues involved in the pairing $\left(n_{b p}\right)$. The following quadratic formula gave the best stable performance:

$$
c_{e v_{a b s}}\left(b p_{t g t}\right)= \begin{cases}\left(0.5-\tilde{p}\left(b p_{t g t}\right)\right)^{2} \cdot n_{b p} & \text { if } \tilde{p}\left(b p_{t g t}\right) \leq 0.5,  \tag{5}\\ -\left(0.5-\tilde{p}\left(b p_{t g t}\right)\right)^{2} \cdot n_{b p} & \text { if } \tilde{p}\left(b p_{t g t}\right)>0.5 .\end{cases}
$$

An additional term has been included in order to stabilize the algorithm in the presence of wrong estimations. This contribution also takes account of the corresponding $\beta$-pair in the template $\left(b p_{t p l}\right)$, for which the estimation error is known to be $1-\tilde{p}\left(b p_{t p l}\right)$. The requirement for this term derives from the assumption that, with the correct alignment, the errors in the estimation of $p$ on the template and target are correlated. Therefore, if $\tilde{p}$ for the template is significantly larger than for the target, we have a strong indicator of a probable error in the alignment. This relative contribution is given by:

$$
c_{e v_{r e l}}\left(b p_{t g t}, b p_{t p l}\right)= \begin{cases}\left(\tilde{p}\left(b p_{t p l}\right)-\tilde{p}\left(b p_{t g t}\right)\right)^{2} \cdot n_{b p} & \text { if } \tilde{p}\left(b p_{t p l}\right)-\tilde{p}\left(b p_{t g t}\right)>0.1  \tag{6}\\ 0 & \text { otherwise }\end{cases}
$$

The total cost for a single $\beta$-pair is then:

$$
\begin{equation*}
c_{e v}\left(b p_{t g t}, b p_{t p l}\right)=\gamma_{a b s} \cdot c_{e v_{a b s}}\left(b p_{t g t}\right)+\gamma_{r e l} \cdot c_{e v_{r e l}}\left(b p_{t g t}, b p_{t p l}\right) \tag{7}
\end{equation*}
$$

where $\gamma_{a b s}$ and $\gamma_{r e l}$ are given as parameters. (Note that in NOBCalign, $\gamma_{a b s}$ and $\gamma_{r e l}$ are set to zero.) The total cost for an alignment is given by the sum of $c_{e v}$, for all the $\beta$-pairs resulting from the assignment of the template structure $\left(S_{t p l}\right)$ to the target $\left(\tilde{S}_{t g t}\right)$ :

$$
\begin{equation*}
c_{b c}\left(A, S_{t p l}\right)=\sum c_{e v}\left(b p_{t g t}, b p_{t p l}\right), \forall b p_{t p l} \in S_{t p l}, b p_{t g t} \in \tilde{S}_{t g t} \tag{8}
\end{equation*}
$$

```
def bc_align(template_seq, target_seq, template_str):
    c_pairs=set()
    for MAX_ITERATIONS times:
        current_solution = bc_search(template_seq, target_seq, c_pairs)
        new_c_pairs = c_pairs + get_c_pairs(current_solution, template_str)
        if len(new_c_pairs) > len(c_pairs):#no new pair found
            c_pairs = new_c_pairs
        else:
            break
    return current_solution
```

Figure S1: The iterative algorithm pseudo-code, in Python-like syntax.

## 2 Minimizing the Cost Function In Detail

A search algorithm is completely defined by:

- The search problem. This is defined by the tuple:
( $S_{0}$, operator-set, goal-test, f),
where $S_{0}$ is the start state; operator-set defines the set of states that can be reached from a given state; goal-test can say whether a given state is the goal or not; $f$ is an evaluation function which gives a score (or cost) for a given path (sequence of states).
- The search strategy. This determines the order in which the nodes are expanded. For instance, a best-first strategy always expands a node with the best value of $f$.

With a global-search algorithm, the best alignment can be found by searching for the path in a tree which optimizes $f$, leading to the end of the sequences.

Using a blind (brute-force) search strategy, many nodes are expanded unnecessarily before finding the solution; this may lead to an explosion in computational cost. The number of expanded nodes is greatly reduced by adopting a heuristic search algorithm such as $\mathrm{A}^{*}$ where the path cost of a given node $n$ is the sum of two terms:

$$
\begin{equation*}
f(n)=g(n)+h(n) \tag{9}
\end{equation*}
$$

$g$ being a path cost function, and $h$ being a heuristic function, expected to estimate the cost from that node to the solution. If the cost increases monotonically along the path and the heuristic function is 'admissible' (i.e. it is an underestimation of the real cost of the solution) the $\mathrm{A}^{*}$ algorithm is guaranteed to find the path with minimum cost. The complexity becomes linear if the estimation given by the heuristic function is exact.

Using the cost function defined in Equation 1 as $g(n)$, a heuristic function can be devised to estimate exactly the first two terms of the cost, but an exact
estimate cannot be given for $c_{b c}\left(A, S_{t p l}\right)$; the complexity rapidly increases with the length of the sequences to be aligned. In order to control the run time, rather than dynamically apply the evaluator during the search, an iterative procedure has been used: at the $i$-th iteration, the pairings found in all $i-1$ previous iterations are evaluated, until a reasonable trade-off is found.

Figure S1 presents the pseudo code for the iterative procedure. The function $b c \_s e a r c h$ performs a search, applying the costs for the pairs obtained for the $\beta$ pairs encountered in the solutions of previous iterations. The iterations continue until convergence, or until an iteration limit is reached.

The A* evaluation function has been used in the alignment search algorithm, with the Iterative-Deepening A* (IDA*) search strategy. In our case, a search state is indicated by $S=[i, j] . i$ and $j$ represent the relative position in the sequences, and can also be viewed as coordinates in a Needleman and Wunschlike cost matrix. The heuristic search problem is given by:

- $S_{0}$ (start state): $[0,0]$
- goal-test: $\left[i_{0}, j_{0}\right], i_{0}=\operatorname{length}\left(P_{1}\right) \wedge j_{0}=\operatorname{length}\left(P_{2}\right)$
- operators: $\left[i_{0}, j_{0}\right] \rightarrow\left\{\left[i_{0}+1, j_{0}+1\right],\left[i_{0}+1, j_{0}\right],\left[i_{0}, j_{0}+1\right]\right\}$ (substitution, insertion, and deletion respectively). Each operation is defined provided that $i \leq$ length $\left(P_{1}\right) \vee j \leq$ length $\left(P_{2}\right)$.
- $g$ (cost function): depends on the path from the start state to the current state. It includes the costs for the substitutions and gaps along the path, and the costs arising from $\beta$-pair evaluations. The cost function is basically $c$ as defined in Equation 1, but for performance reasons, the values are rounded to the nearest integer.
- $h$ (heuristic function): the heuristic function is the estimated cost for the remaining part of the sequences from the current state. A matrix $H_{P_{1}, P_{2}}$ gives the estimation: $h([i, j])=H_{P_{1}, P_{2}}(i, j)$ and is constructed similarly to a Needleman and Wunsch matrix, minimizing the sum of the terms $c_{n w}$ and $c_{\beta i}$.


## 3 Results

| Fold | Accuracy | Precision | Recall | MCC $^{\dagger}$ |
| :--- | :--- | :--- | :--- | :--- |
| 1 | 0.781 | 0.765 | 0.807 | 0.563 |
| 2 | 0.783 | 0.774 | 0.797 | 0.565 |
| 3 | 0.795 | 0.777 | 0.821 | 0.592 |
| 4 | 0.784 | 0.777 | 0.802 | 0.568 |
| 5 | 0.784 | 0.768 | 0.812 | 0.569 |
| 6 | 0.790 | 0.764 | 0.840 | 0.582 |
| 7 | 0.778 | 0.770 | 0.797 | 0.556 |
| AVG | 0.785 | 0.771 | 0.811 | 0.571 |

Table S1: Results for BCeval in a 7 -fold cross validation test on the dataset TRAINCH. ${ }^{\dagger} \mathrm{MCC}=$ Matthews' Correlation Coefficient.

