# The Potts Model and the Multi-Way Cut Problem 

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## 1. Motivation

Recall the energy function $E(f)$. In terms of the Potts model we may informally write the energy function as

$$
E(f)=\sum_{p \in P} C(p, f(p))+\lambda(\# \text { discontinuities }) .
$$

The number of discontinuities may also be thought of as the number of disconnected components. This is what we strive for in the Multi-Way Cut (MWC) problem. Our goal is to separate terminal [label] nodes from pixel nodes through inspection of wieghts (Fig. 1). We are therefore looking for the cheapest multiway cut.


Figure 1
We know that solving the Potts problem is NP-hard, but so is MWC. What we want is to turn an instance of the Potts problem into a MWC, and vice-versa. If that is the case, then a 2-Approximation algorithm (2-APPR) for MWC would suggest $\exists 2$-APPR for the Potts problem. Before we derive this, let's examine MWC some more.

The weights on the arcs in the graph, such as $w_{x}$ (Fig. 1) arise from the "smoothness" term in $E(f)$. The weights among the pixels, i.e. $w_{y}$, are from the "data" term $\lambda$ in $E(f)$. These pixel-pixel arcs are also known as "n-links", whereas the label-pixel arcs are "d-links".

MWC is defined by the minimum cut property. So for a graph $G=(V, E)$, we look for a set $C \subset E$ which separates the vertex sets $S$ and $T$ such that $V=S \cup T$. It is important to realize that $C$ has no subsets that can do this as well.

But suppose we are given the graph in Fig. 2. This would not be a MWC! The reason is that we can't have $(p, q) \in C \wedge(q, r) \in C$. If they both belonged to $C$ then $\exists$ path $\langle\alpha, q, r, \beta\rangle$. In the end, if we do have a MWC then a pixel $p \in S=P$ is connected to no more than 1 label (terminal) $l \in T$. Conceptually, one may envision this as each terminal grabbing a piece of an image.


Figure 2
In order to make our graph behave correctly we want to make all the arcs (edges) non-negative. For a d-link we have some value $K-c(p, \alpha)$ where $c$ is a cost function. To ensure this we choose some big value for $K$. One example is $K>\max (c(p, \alpha)) \forall p, \alpha$. This is commonly overlooked because we wish to cut the light weights, and not vice versa.

## 2. Approximation for the Potts Model

From now on let us write $|C|$ as the summation of the weights in the multiway cut $C$. We then have the sum of $n$-links and d-links to equal the energy function (plus a constant). In other words,

$$
|C|=E\left(f^{C}\right)+\text { const }
$$

where $f^{C}$ denotes the function that assigns a label $l$ to all its pixels. Now consider Fig. 3 as a snapshot of a much larger net of pixels. Calculating the cost of d-links out of $p$ procedes as follows:

$$
\begin{aligned}
|C| & =\sum_{p \in P}\left[\sum_{L \neq f^{C}(p)} K-c\left(p, f^{C}(p)\right)\right] \\
& =\sum_{p \in P}(m-1) K-\sum_{p \in P}^{\sum_{p} c\left(p, f^{C}(p)\right)} \\
& =\sum_{p \in P}(m-1) K+\underbrace{c\left(p, f^{C}(p)\right)-\sum_{l \in L} c(p, l)} \quad \text { (cost of labels ) } \\
& =\sum_{p \in P} c\left(p, f^{C}(p)\right)+\text { const }
\end{aligned}
$$

We now have an approximation for the Potts model. However, we are looking for a 2-APPR to the MWC, so we can take advantage of a key notion, that of an isolating cut.


Figure 3

A method to generate such a cut can be described in 3 steps. $\forall$ terminals do:
(1) pick a terminal $\alpha$ as a source
(2) link all others to vertex (super-sink) $t$ with $\infty$ cost arcs (i.e. can't be cut)
(3) run the MINCUT algorithm

Note that 2 things may go wrong with the above procedure.
(1) Dangling nodes (pixels) may exist. SOLUTION: Pick a [random] terminal for it.
$\left(2^{*}\right)$ Overlapping of the labeled regions may occur (Fig. 4). SOLUTION:
(Easy) Can't really happen. Keep reading for the real problem.


Figure 4
This isolation heuristic gives a 2-APPR for MWC. But $E\left(f^{C}\right) \leq E\left(f^{C^{*}}\right)$ since $|C| \leq 2\left|C^{*}\right|$, and we see that $E\left(f^{C}\right) \leq 2 E\left(f^{C^{*}}\right)+$ const given that $C^{*}$ is the minimum multiway cut. That means we can't get an optimal labeling within a constant energy factor. This is actually the $2^{\text {nd }}$ problem, not $2^{*}$ as listed above.

## 3. Swap Moves

Maybe we can get a good APPR using swap moves. Specifically we're asking the following:

Given a labeling $F$ and $\alpha, \beta$ pairs, can we find an average minimization $E\left(f^{\prime}\right)$, with $f^{\prime}$ near $f$ within1 $\alpha-\beta$ swap move?

A swap move is a mapping $f \mapsto f^{\prime}$ if $f(p) \notin\{\alpha, \beta\} \rightarrow f^{\prime}(p)=f(p)$. A special case of this is a standard Simulated Annealing move, which happens to be just a degenerate swap move. In an algorithm we ignore all but the ( $\alpha, \beta$ ) pair. This is when the two labels "fight it out." So to minimize $f$ we define the procedure:

$$
\left.\operatorname{MIN}(f) \equiv \quad \begin{array}{ll}
\forall(\alpha, \beta) & \text { find cheapest } f^{\prime}, \\
& \underbrace{\text { if } E(f)>E\left(f^{\prime}\right) \text { then } f=f^{\prime}}
\end{array}\right\} \text { cycle }
$$

iteration

## 4. Expansion Moves

But this is not the APPR we want due to the choice of arbitrary swaps. Instead we will
utilize expansion moves. These will lead us to a 2-APPR.

$$
\begin{array}{lll}
\text { EXPANSION MOVE }(\alpha: \text { expansion }) \equiv \text { if } \forall p & f(p)=\alpha \rightarrow f^{\prime}(p)=\alpha \\
& f^{\prime}(p) \neq \alpha \rightarrow f^{\prime}(p)=f(p)
\end{array}
$$

## 5. Concluding Remarks

a) The 3 moves covered can be categorized as

b) These moves are powerful - with EXPANSION we can get to the global minimum $f \mapsto f^{\prime}\left(\mapsto f^{*}\right)$ in $m$ EXP moves irrespective of the huge label space.

