## A Proof of Lemma 4.2

The regularization is:

$$
\begin{align*}
\sum_{i=1}^{N} \sum_{j=1}^{N}\left\|C_{i}-C_{j}\right\|_{2}^{2} & =\sum_{i=1}^{N} \sum_{j=1}^{N}\left(C_{i}^{T} C_{i}-2 C_{i}^{T} C_{j}+C_{i}^{T} C_{i}\right) \\
& =2 N \sum_{i=1}^{N} C_{i}^{T} C_{i}-2 \sum_{i=1}^{N} \sum_{j=1}^{N} C_{i}^{T} C_{j}  \tag{21}\\
& =2 N \sum_{i=1}^{N} C_{i}^{T}\left(C_{i}-\frac{1}{N} \sum_{j=1}^{N} C_{j}\right)=2 N \sum_{i=1}^{N} C_{i}^{T}\left(C_{i}-\bar{C}\right) \\
& \stackrel{(*)}{=} 2 N \sum_{i=1}^{N}\left\|C_{i}-\bar{C}\right\|_{2}^{2},
\end{align*}
$$

where $(*)$ derives from the equality $\sum_{i=1}^{N} \bar{C}^{T}\left(C_{i}-\bar{C}\right)=0$. Hence, the regularization is used to maximize the sample variance. Assume that only samples are accessible to the target distribution $\operatorname{Dir}(\beta)$, we consider the variance instead (i.e., $\left.\mathbb{E}_{C_{i} \sim \operatorname{Dir}(\beta)}\left[\sum_{i=1}^{N}\left\|C_{i}-\bar{C}\right\|_{2}^{2}\right]\right)$. To simplify the notation (i.e., ignore the constant),

$$
\begin{equation*}
\mathbb{E}_{x \sim \operatorname{Dir}(\beta)}\left[(x-\mathbb{E}[x])^{T}(x-\mathbb{E}[x])\right]=\sum_{k=1}^{K} \operatorname{Var}\left(x_{k}\right)=\sum_{k=1}^{K} \frac{\beta_{k}\left(\beta_{0}-\beta_{k}\right)}{\beta_{0}^{2}\left(\beta_{0}+1\right)} \tag{22}
\end{equation*}
$$

Here, we have $\beta_{0}=\sum_{k=1}^{K} \beta_{k}$. We want to investigate the effect of adding this regularization w.r.t. to parameter $\beta$. Alternatively, we consider the optimization problem as below,

$$
\begin{align*}
& \max _{\beta} \sum_{k=1}^{K} \frac{\beta_{k}\left(\beta_{0}-\beta_{k}\right)}{\beta_{0}^{2}\left(\beta_{0}+1\right)}  \tag{23}\\
& \text { s.t. } \beta_{k} \geq 0, \forall k \in[K] .
\end{align*}
$$

Then, we have $t^{*}=\sum_{k=1}^{K} \beta_{k}^{*}$ where $\beta^{*}$ is the optimal point. We take a step towards the following convex problem,

$$
\begin{gather*}
\min _{\beta}-\sum_{k=1}^{K} \beta_{k}\left(t^{*}-\beta_{k}\right) \\
\text { s.t. } \sum_{k=1}^{K} \beta_{k}=t^{*},  \tag{24}\\
\quad \beta_{k} \geq 0, \forall k \in[K] .
\end{gather*}
$$

As the slater condition holds, KKT condition is necessary and sufficient. The so-called augmented Lagrangian function is

$$
L(\beta, \nu, \pi)=-\sum_{k=1}^{K} \beta_{k}\left(t^{*}-\beta_{k}\right)+\nu\left(\sum_{k=1}^{K} \beta_{k}-t^{*}\right)-\sum_{k=1}^{K} \pi_{k} \beta_{k} .
$$

The KKT condition is

$$
\left\{\begin{array}{l}
-t^{*}+2 \beta_{k}+\nu-\pi_{k}=0, \forall k \in[K]  \tag{25}\\
\sum_{k=1}^{K} \beta_{k}-t^{*}=0 \\
\pi_{k} \beta_{k}=0, \beta_{k} \geq 0, \pi_{k} \geq 0 \forall k \in[K]
\end{array}\right.
$$

Consider the case $\pi_{k}=0, \beta_{k}>0$, we have $\beta_{k}^{*}=\frac{t^{*}}{K}, \nu^{*}=\frac{K-2}{K} t^{*}$. We come back to the original problem,

$$
\sum_{k=1}^{K} \frac{\beta_{k}\left(\beta_{0}-\beta_{k}\right)}{\beta_{0}^{2}\left(\beta_{0}+1\right)}=\frac{K-1}{K t^{*}} .
$$

Overall, maximizing this component enforces $t^{*} \rightarrow 0$ and all equal parameters for the Dirichlet distributions.

## B Proof of Proposition 5.1

The distance between an arbitrary spectral filter $g(\lambda)$ and the ideal low pass filter $g_{\mathrm{id}}(\lambda)$ in Eq. 4 is defined as,

$$
\begin{equation*}
\text { Distance }\left(g, g_{\mathrm{id}}\right)=\int_{0}^{\lambda_{K}}(1-g(\lambda))^{2} d \lambda+\int_{\lambda_{K}}^{2}(0-g(\lambda))^{2} d \lambda \tag{26}
\end{equation*}
$$

Intuitively, this definition computes the squared Euclidean distance between $g(\cdot)$ and $g_{\mathrm{id}}(\cdot)$. Thus, the distance between $\operatorname{GCN} g_{c}(\cdot)$ and the ideal low pass $g_{\mathrm{id}}(\cdot)$ is:

$$
\begin{align*}
\operatorname{Distance}\left(g_{c}, g_{\mathrm{id}}\right) & =\int_{0}^{\lambda_{K}}(1-(1-\lambda))^{2} d \lambda+\int_{\lambda_{K}}^{2}(0-(1-\lambda))^{2} d \lambda  \tag{27}\\
& =\lambda_{K}^{2}-\lambda_{K}+\frac{2}{3}
\end{align*}
$$

The distance between Heatts $g_{s}(\cdot)$ and the ideal low pass $g_{\mathrm{id}}(\cdot)$ :

$$
\begin{equation*}
\text { Distance }\left(g_{s}, g_{\mathrm{id}}\right)=\int_{0}^{\lambda_{K}}\left(-s \lambda+\frac{1}{2} s^{2} \lambda^{2}-\frac{1}{6} s^{3} \lambda^{3}\right)^{2} d \lambda+\int_{\lambda_{K}}^{2}\left(1-s \lambda+\frac{1}{2} s^{2} \lambda^{2}-\frac{1}{6} s^{3} \lambda^{3}\right)^{2} d \lambda \tag{28}
\end{equation*}
$$

Our purpose is to derive value range of $s$ such that $\operatorname{Distance}\left(g_{s}, g_{\mathrm{id}}\right)$ is always smaller than Distance $\left(g_{c}, g_{\mathrm{id}}\right)$.

$$
\begin{equation*}
\operatorname{Distance}\left(g_{s}, g_{\mathrm{id}}\right)-\operatorname{Distance}\left(g_{c}, g_{\mathrm{id}}\right) \geq 0 \tag{29}
\end{equation*}
$$

The solution is $0.672 \leq s \leq 1.321$
As shown in Figure 4, Heatts is always closer to the ideal low pass $g_{\text {id }}(\cdot)$ when $s \in[0.672,1.321]$.
Table 3: Statistics of data sets used in graph clustering

| Data | Nodes | Edges | Classes | features |
| :---: | :---: | :---: | :---: | :---: |
| Pubmed | 19,717 | 44,338 | 3 | 500 |
| Citeseer | 3,327 | 4,732 | 6 | 3,703 |
| Wiki | 2,405 | 17,981 | 17 | 4,973 |



Figure 4: The distance between spectral filters and the ideal low pass

