## Problem 1 (Coherent capacity: Symmetric assumption)

(a). The capacity of the MIMO channel with receiver CSI is given by

$$
\begin{aligned}
C & =\max _{\mathbf{K}_{x}: \operatorname{Tr}\left(\mathbf{K}_{x}\right) \leq P} \mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H} \mathbf{K}_{x} \mathbf{H}^{*}\right)\right] \\
& =\max _{\mathbf{K}_{x}: \operatorname{Tr}\left(\mathbf{K}_{x}\right) \leq P} \mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{U}_{r} \mathbf{H}^{\mathrm{a}} \mathbf{U}_{t}^{*} \mathbf{K}_{x} \mathbf{U}_{t} \mathbf{H}^{\mathrm{a}} \mathbf{U}_{r}^{*}\right)\right] \\
& \stackrel{(i)}{=} \max _{\mathbf{K}_{x}: \operatorname{Tr}\left(\mathbf{K}_{x}\right) \leq P} \mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \mathbf{U}_{t}^{*} \mathbf{K}_{x} \mathbf{U}_{t} \mathbf{H}^{\mathrm{a} *} \mathbf{U}_{r}^{*} \mathbf{U}_{r}\right)\right] \\
& =\max _{\mathbf{K}_{x}: \operatorname{Tr}\left(\mathbf{K}_{x}\right) \leq P}\left[\operatorname{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \mathbf{U}_{t}^{*} \mathbf{K}_{x} \mathbf{U}_{t} \mathbf{H}^{\mathrm{a} *}\right)\right]\right.
\end{aligned}
$$

(i) follows from the identity $\operatorname{det}(I+A B)=\operatorname{det}(I+B A)$.
(b). We can always consider the covariance matrix of the form $\mathbf{K}_{x}=\mathbf{U}_{t} \tilde{\mathbf{K}}_{x} \mathbf{U}_{t}^{*}$ where $\tilde{\mathbf{K}}_{x}$ is also a covariance matrix satisfying the total power constraint.

$$
\begin{aligned}
C & =\max _{\tilde{\mathbf{K}}_{x}: \operatorname{TT}\left(\tilde{\mathbf{K}}_{x}\right) \leq P} \mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \mathbf{U}_{t}^{*} \mathbf{K}_{x} \mathbf{U}_{t} \mathbf{H}^{\mathrm{a} *}\right)\right] \\
& =\max _{\tilde{\mathbf{K}}_{x}: \operatorname{Tr}\left(\tilde{\mathbf{K}}_{x}\right) \leq P} \mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \tilde{\mathbf{K}}_{x} \mathbf{H}^{\mathbf{a} *}\right)\right]
\end{aligned}
$$

Define a diagonal matrix $\Pi_{i}$ with -1 in the $i^{\text {th }}$ position and 1 in the remaining positions. The entries of $\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}$ equal those of $\tilde{\mathbf{K}}_{x}$ except in the off diagonal positions in the $i^{\text {th }}$ row and the $i^{\text {th }}$ column where the sign is reversed. The matrix $\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}$ is a covariance matrix satisying the power constraint, i.e., $\operatorname{Tr}\left\{\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}\right\}=\operatorname{Tr}\left\{\tilde{\mathbf{K}}_{x}\right\}$. If we denote $R\left(\tilde{\mathbf{K}}_{x}\right)$ to be

$$
R\left(\tilde{\mathbf{K}}_{x}\right)=\mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \tilde{\mathbf{K}}_{x} \mathbf{H}^{\mathrm{a} *}\right)\right],
$$

then

$$
\begin{aligned}
R\left(\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}\right) & =\mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*} \mathbf{H}^{\mathrm{a} *}\right)\right] \\
& =\mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}}\left(\mathbf{H}^{\mathrm{a}} \Pi_{i}\right) \tilde{\mathbf{K}}_{x}\left(\mathbf{H}^{\mathrm{a}} \Pi_{i}\right)^{*}\right)\right] \\
& \stackrel{(i i)}{=} \mathbb{E}\left[\log \operatorname{det}\left(I_{M_{r}}+\frac{1}{N_{0}} \mathbf{H}^{\mathrm{a}} \tilde{\mathbf{K}}_{x} \mathbf{H}^{\mathbf{a} *}\right)\right] \\
& =R\left(\tilde{\mathbf{K}}_{x}\right)
\end{aligned}
$$

where (ii) follows from the fact that, since the columns of $\mathbf{H}^{\mathbf{a}}$ are independent and their distribution symmetric, $\mathbf{H}^{\mathbf{a}}$ and $\mathbf{H}^{\mathbf{a}} \Pi_{i}$ have the same distribution. From the concavity of the $\log \operatorname{det}(\cdot)$
function, it follows that

$$
\begin{aligned}
R\left(\tilde{\mathbf{K}}_{x}\right) & =\frac{1}{2} R\left(\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}\right)+\frac{1}{2} R\left(\tilde{\mathbf{K}}_{x}\right) \\
& =R\left(\frac{1}{2}\left(\tilde{\mathbf{K}}_{x}+\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}\right)\right)
\end{aligned}
$$

The entries of the matrix $\frac{1}{2}\left(\tilde{\mathbf{K}}_{x}+\Pi_{i} \tilde{\mathbf{K}}_{x} \Pi_{i}^{*}\right)$ are equal to those in $\tilde{\mathbf{K}}_{x}$ except in the off diagonal positions in the $i^{\text {th }}$ row and column, where the entries are zero. Iterating the above process $M_{t}$ times for $i=1, \ldots, M_{t}$, we find that the optimal $\tilde{\mathbf{K}}_{x}$ is diagonal which proves our claim.

## Problem 2 (Universal code design criterion for the MISO channel)

(a). The $Q(\cdot)$ function is decreasing in its argument. The error probability is maximum for the $\mathbf{h}$ for which $\left\|\mathbf{h}^{*}\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)\right\|$ is minimum subject to $\|\mathbf{h}\|^{2} \geq \frac{M_{t}\left(2^{R}-1\right)}{S N R}$

$$
\begin{aligned}
\left\|\mathbf{h}^{*}\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)\right\|^{2} & =\mathbf{h}^{*}\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)^{*} \mathbf{h} \\
& =\mathbf{h}^{*} \mathbf{U} \Lambda_{A-B} \mathbf{U}^{*} \mathbf{h} \\
& =\tilde{\mathbf{h}}^{*} \Lambda_{A-B} \tilde{\mathbf{h}}
\end{aligned}
$$

Since $\tilde{\mathbf{h}}=\mathbf{h}^{*} \mathbf{U}$ is distributed as $\mathbf{h}$,

$$
\begin{aligned}
\min _{\mathbf{h}:\|\mathbf{h}\|^{2} \geq \frac{M_{t}\left(2^{R}-1\right)}{S N R}}\left\|\mathbf{h}^{*}\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)\right\|^{2} & =\min _{\mathbf{h}:\|\mathbf{h}\|^{2} \geq \frac{M_{t}\left(2^{R}-1\right)}{S N R}} \mathbf{h}^{*} \Lambda_{A-B} \mathbf{h} \\
& =\frac{M_{t}\left(2^{R}-1\right)}{S N R} \min _{\mathbf{h}:\|\mathbf{h}\|^{2}=1} \sum_{i}\left|h_{i}\right|^{2} \lambda_{i}^{2} \\
& \geq \frac{M_{t}\left(2^{R}-1\right)}{S N R} \lambda_{1}^{2}
\end{aligned}
$$

where $\lambda_{1}$ is the smallest singular value of $\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)$. The minimum error probability is given by

$$
\begin{aligned}
\max _{\mathbf{h}:\|\mathbf{h}\|^{2} \geq \frac{M_{t}\left(2^{R}-1\right)}{S N R}} Q\left(\frac{\left\|\mathbf{h}^{*}\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)\right\|}{\sqrt{2}}\right) & =Q\left(\sqrt{\frac{\lambda_{1}^{2} M_{t}\left(2^{R}-1\right)}{2 S N R}}\right) \\
& =Q\left(\sqrt{\frac{1}{2} \tilde{\lambda}_{1}^{2} M_{t}\left(2^{R}-1\right)}\right)
\end{aligned}
$$

where $\tilde{\lambda}_{1}$ is the smallest singular value of $\frac{1}{\sqrt{S N R}}\left(\mathbf{X}_{A}-\mathbf{X}_{B}\right)$.
(b).

$$
\begin{aligned}
& Q\left(\sqrt{\frac{\lambda_{1}^{2} M_{t}\left(2^{R}-1\right)}{2 S N R}}\right)<e^{-\frac{\lambda_{1}^{2} M_{t}\left(2^{R}-1\right)}{4 S N R}} \\
& \quad \approx e^{-\lambda_{1}^{2} S N R^{-(1-r)}}
\end{aligned}
$$

where the approximation is made on the scale of $S N R$. As long as $\lambda_{1}^{2}>S N R^{1-r}$, the error probability goes down exponentially with $S N R$.

## Problem 3 (Diversity-Multiplexing tradeoff - Alamouti scheme over the $2 \times M_{r}$ MIMO)

(a). The received vector at the first time instant is given by

$$
\mathbf{y}[1]=\mathbf{h}_{1} u_{1}+\mathbf{h}_{2} u_{2}+\mathbf{z}[1]
$$

and at the second time instant is given by

$$
\mathbf{y}[2]=\mathbf{h}_{1}\left(-u_{2}^{*}\right)+\mathbf{h}_{2} u_{1}^{*}+\mathbf{z}[2]
$$

This can be rewritten as

$$
\binom{\mathbf{y}[1]}{\left(\mathbf{y}[2]^{*}\right)^{\top}}=\left(\begin{array}{cc}
\mathbf{h}_{1} & \mathbf{h}_{2} \\
\left(\mathbf{h}_{2}^{*}\right)^{\top} & -\left(\mathbf{h}_{1}^{*}\right)^{\top}
\end{array}\right)\binom{u_{1}}{u_{2}}+\binom{\mathbf{z}[1]}{\left(\mathbf{z}[2]^{*}\right)^{\top}}
$$

(b). Define $\mathbf{H}$ to be the matrix with columns $\mathbf{h}_{1}$ and $\mathbf{h}_{2}$ and let $\|\mathbf{H}\|^{2}=\left\|\mathbf{h}_{1}\right\|^{2}+\left\|\mathbf{h}_{2}\right\|^{2}$ Projecting the output along the direction of $\binom{\mathbf{h}_{1}}{\left(\mathbf{h}_{2}^{*}\right)^{\top}}$ gives

$$
\begin{aligned}
r_{1} & =\frac{1}{\|\mathbf{H}\|}\left(\begin{array}{ll}
\mathbf{h}_{1}^{*} & \left(\mathbf{h}_{2}\right)^{\top}
\end{array}\right)\binom{\mathbf{y}[1]}{\left(\mathbf{y}[2]^{*}\right)^{\top}} \\
& =\|\mathbf{H}\| u_{1}+w_{1}
\end{aligned}
$$

where $w_{1} \sim \mathcal{C} \eta(0,1)$. Likewise projecting the output along the direction of $\binom{\mathbf{h}_{2}}{-\left(\mathbf{h}_{1}^{*}\right)^{\top}}$ gives

$$
\begin{aligned}
r_{2} & =\frac{1}{\|\mathbf{H}\|}\left(\begin{array}{ll}
\mathbf{h}_{2}^{*} & \left.-\left(\mathbf{h}_{1}\right)^{\top}\right)\binom{\mathbf{y}[1]}{\left(\mathbf{y}[2]^{*}\right)^{\top}} \\
& =\|\mathbf{H}\| u_{2}+w_{2}
\end{array},\right.
\end{aligned}
$$

where $w_{2} \sim \mathcal{C} \eta(0,1)$. We have made use of the fact that the two columns of $\mathbf{H}$ are orthogonal to separate the signals $u_{1}$ and $u_{2}$ at the receiver.
(c). The channel corresponding to either stream $u_{i}$ is a scalar channel with gain $\|\mathbf{H}\|$ and by reasoning similar to the previous two questions, the diversity gain at rate $r \log S N R$ is given by $2 M_{r}(1-r)$.

## Problem 4 (Diversity-Multiplexing tradeoff - Repetition coding over $L$ parallel channels)

The output of the $i^{\text {th }}$ channel is given by

$$
y_{i}=h_{i} u+z_{i}
$$

Collecting the $L$ outputs, we have

$$
\mathbf{y}=\left(\begin{array}{c}
y_{1} \\
y_{2} \\
. . \\
. . \\
y_{L}
\end{array}\right)=\left(\begin{array}{c}
h_{1} \\
h_{2} \\
. . \\
. . \\
h_{L}
\end{array}\right) u+\left(\begin{array}{c}
z_{1} \\
z_{2} \\
. . \\
. . \\
z_{L}
\end{array}\right)
$$

Projecting the output vector in the direction of $\left(\begin{array}{c}h_{1} \\ h_{2} \\ . . \\ . . \\ h_{L}\end{array}\right)$ gives

$$
\begin{aligned}
\tilde{y} & =\frac{1}{\|\mathbf{h}\|}\left(\begin{array}{lllll}
h_{1}^{*} & h_{2}^{*} & . . & . . & h_{L}^{*}
\end{array}\right) \mathbf{y} \\
& =\|\mathbf{h}\| u+\tilde{z}
\end{aligned}
$$

where $\tilde{z} \sim \mathcal{C} \eta(0,1)$ and $\|\mathbf{h}\|^{2}=\sum_{l}\left|h_{l}\right|^{2}$. The outage probability at rate $r \log S N R$ for this effective scalar channel is given by

$$
\begin{aligned}
\operatorname{Pr}\left\{\log \left(1+\|\mathbf{h}\|^{2} S N R\right)<r \log S N R\right\} & =\operatorname{Pr}\left\{\|\mathbf{h}\|^{2}<\frac{S N R^{r}-1}{S N R}\right\} \\
& \approx \operatorname{Pr}\left\{\|\mathbf{h}\|^{2}<S N R^{-(1-r)}\right\} \\
& \approx S N R^{-L(1-r)}
\end{aligned}
$$

where the two approximations follow for large enough $S N R$ and since $\|\mathbf{h}\|^{2} \sim \chi_{2 L}^{2}$, so $\operatorname{Pr}\left(\|\mathbf{h}\|^{2}<\varepsilon\right) \approx$ $\varepsilon^{L}$. Since $r$ is the rate achievable over $L$ channel uses, the effective rate $\tilde{r}=\frac{r}{L}$. In terms of this effective rate, the diversity gain is given by $L(1-L \tilde{r})$.

## Problem 5 (Diversity-Multiplexing tradeoff - V-Blast with annuling)

The output at the receiver is given by

$$
\mathbf{y}=\mathbf{h}_{k} x_{k}+\sum_{i \neq k} \mathbf{h}_{i} x_{i}+\mathbf{z}
$$

The decorrelator projects the output in the subspace orthogonal to the columns $\left\{\mathbf{h}_{i}\right\}_{i \neq k}$. If we call the projection matrix $\mathbf{Q}_{k}$, the projection is given by

$$
\begin{aligned}
\tilde{\mathbf{y}_{k}} & =\mathbf{Q}_{k} \mathbf{y} \\
& =\mathbf{Q}_{k} \mathbf{h}_{k} x_{k}+\mathbf{Q}_{k} \mathbf{z}
\end{aligned}
$$

Projecting $\tilde{\boldsymbol{y}_{k}}$ along $\mathbf{Q}_{k} \mathbf{h}_{k}$ gives the equivalent scalar channel where the achievable rate per stream $k$ is given by $\log \left(1+\frac{S N R}{n_{t}}\left\|\mathbf{Q}_{k} \mathbf{h}_{k}\right\|^{2}\right)$. In problem 3 of homework 2, we saw that $\mathbf{Q}_{k}$ has rank $n_{r}-\left(n_{t}-1\right)$. Therefore $\left\|\mathbf{Q}_{k} \mathbf{h}_{k}\right\|^{2} \sim \chi_{2\left(n_{r}-n_{t}+1\right)}^{2}$. Therefore the diversity gain at multiplexing gain of $r_{k}$ is given by $\left(n_{r}-n_{t}+1\right)\left(1-r_{k}\right)$. Since we assume the streams to have equal rate, the net rate $r=\sum_{k} r_{k}$, or equivalently, $r_{k}=\frac{r}{n_{t}}$. So the diversity gain is equivalently given by $\left(n_{r}-n_{t}+1\right)\left(1-\frac{r}{n_{t}}\right)$.

## Problem 6 (Diversity multiplexing tradeoff using superposition codes)

(a). We can assume that $T \rightarrow \infty$, and therefore get the D-M tradeoff $d(r)=1-r$. Note that in fact we do not need $T$ to be too large. As we have seen in the class uncoded QAM achieves the D-M tradeoff of this channel with $T=1$.
(b).

$$
\begin{aligned}
P_{\text {out }}\left(r_{H}, r_{L}, \mathrm{SNR}\right) & =\operatorname{Pr}\left[\log \left(1+\mathrm{SNR}^{1-\beta}\left|h^{(b)}\right|^{2}+\mathrm{SNR}\left|h^{(b)}\right|^{2}\right)<r_{L} \log \mathrm{SNR}+r_{H} \log \mathrm{SNR}\right] \\
& =\operatorname{Pr}\left[\left|h^{(b)}\right|^{2}<\frac{\mathrm{SNR}^{r_{L}+r_{H}}-1}{\mathrm{SNR}+\mathrm{SNR}^{1-\beta}}\right] \\
& \doteq \mathrm{SNR}^{-\left(1-r_{L}-r_{H}\right)} .
\end{aligned}
$$

Therefore, $\tilde{d}\left(r_{L}, r_{H}\right)=1-r_{L}-r_{H}$.
(c). Since we use successive decoder, we have to consider the weak message as noise when we decode the first one. Let $\left|h^{(b)}\right|^{2} \doteq \mathrm{SNR}^{-\alpha}$ for some $\alpha \in \mathbb{R}$. Therefore we have

$$
\begin{aligned}
\operatorname{SINR}_{H} & =\frac{\operatorname{SNR}\left|h^{(b)}\right|^{2}}{\operatorname{SNR}^{1-\beta}\left|h^{(b)}\right|^{2}+1} \\
& =\frac{\operatorname{SNR}^{1-\alpha}}{\operatorname{SNR}^{1-\beta-\alpha}+1} \\
& \doteq \begin{cases}\operatorname{SNR}^{\beta} & \text { if } 1-\alpha-\beta>0 \\
\operatorname{SNR}^{1-\alpha} & \text { if } 1-\alpha-\beta \leq 0\end{cases} \\
& =\operatorname{SNR}^{\text {min }}(1-\alpha, \beta) .
\end{aligned}
$$

Hence,

$$
\begin{aligned}
P_{\text {out }}\left(r_{H}, \mathrm{SNR}\right)= & \operatorname{Pr}\left[\log \left(1+\mathrm{SINR}_{H}\right)<r_{H} \log \mathrm{SNR}\right] \\
= & \operatorname{Pr}\left[\log \left(1+\mathrm{SNR}^{\min (1-\alpha, \beta)}\right)<r_{H} \log \mathrm{SNR}\right] \\
= & \operatorname{Pr}\left[\log \left(1+\mathrm{SNR}^{\beta}\right)<r_{H} \log \mathrm{SNR} \mid \alpha<1-\beta\right] \cdot \operatorname{Pr}[\alpha<1-\beta] \\
& +\operatorname{Pr}\left[\log \left(1+\mathrm{SNR}^{1-\alpha}\right)<r_{H} \log \operatorname{SNR}, \alpha>1-\beta\right]
\end{aligned}
$$

It is clear that for $\beta=1$, we get

$$
P_{\text {out }}\left(r_{H}, \mathrm{SNR}\right)=\operatorname{Pr}\left[\log \left(1+\mathrm{SNR}^{1-\alpha}\right)<r_{H} \log \mathrm{SNR}\right] \doteq \mathrm{SNR}^{-\left(1-r_{H}\right)}
$$

For $\beta<1$, we can write

$$
\begin{aligned}
P_{\text {out }}\left(r_{H}, \mathrm{SNR}\right) & =\mathbf{1}_{\left[\beta<r_{H}\right]}\left[1-\mathrm{SNR}^{-(1-\beta)}\right]+\mathrm{SNR}^{-\max \left(1-r_{H}, 1-\beta\right)} \\
& \doteq \begin{cases}1 & \text { if } r_{H}>\beta \\
\mathrm{SNR}^{-\left(1-r_{H}\right)} & \text { if } r_{H} \leq \beta .\end{cases}
\end{aligned}
$$

(d). It is clear that

$$
d_{H}=\lim _{S N R \rightarrow \infty} \frac{\log P_{\text {out }}\left(M_{H}, S N R\right)}{\log S N R}= \begin{cases}0 & \text { if } r_{H}>\beta \\ 1-r_{H} & \text { if } r_{H}>\beta .\end{cases}
$$

(e). For $\beta>r_{H}$, we have $d_{H}=1-r_{H}$, which is the same as in part (a).

