## Approximating Large Matrix $A$

1. Importance and Motivation. Using SVD we can get the approximation of $A$ in the following way.

Let $A$ be our matrix, defined as a set of column vectors. Establish $G$ as a set of Gaussian random row vectors. Define their product $Y$.

$$
\begin{aligned}
Y & =A G \\
& =\left[\begin{array}{lll}
a_{1} & \ldots & a_{n}
\end{array}\right]\left[\begin{array}{c}
g_{1} \\
\vdots \\
g_{n}
\end{array}\right]
\end{aligned}
$$

Now derive $Q$ from QR decomposition, $Q=\mathrm{qr}(\mathrm{Y}, 0)$. We can define $B=Q^{*} A$, with decomposition $B=$ $\hat{U} D V^{*}$, and we claim that

$$
\begin{aligned}
Q Q^{*} A & \approx A \\
Q B & \approx A \\
Q-\operatorname{svd}(\mathrm{B}) & \approx A
\end{aligned}
$$

This approximation of $A$ can be widely used in a ton of applications, not just SVD! Therefore it's important to understand its derivation and usefulness.
2. Properties and Definition of $Q$. We have shown that $Q Q^{*} A \approx A$, and we can examine the properties of $Q Q^{*}$. We claim that $Q Q^{*}$ is actually a projector onto the range of $Q$.
To be a projector, the following properties must be satisfied.

1. $\hat{P}^{2}=\hat{P}$
2. $\hat{P} \vec{v}=\vec{v}$ for some vector $\vec{v}$.

These can be trivially shown using the definition of $\hat{P}$, which implies the following two statements are equivalent.

- $\operatorname{range}(A) \subseteq \operatorname{range}(Q)$
- $A=Q Q^{*} A$.

In a sense, $Q$ captures the range of $A$.
We can see that these properties hold as long as $Q \underbrace{Q^{*} A}_{B} \approx A$ and $B$ is smaller than $A$.
3. Determining $Q$. We've defined $Q$ to be the result of QR decomposition on our $Y$ matrix (our random sampling of $A$ ), but we have to be careful how we define that random sampling.

$$
Y=\begin{array}{cc}
A & G \\
m \times n & n \times(k+p)
\end{array}
$$

Much of the algorithm is now determined by $k+p$.

- If $k+p$ is small, $A$ isn't sampled enough and our approximation is no longer accurate.
- If $k+p$ is large, $B$ grows large and we've lost the reason why we're trying to approximate $A$ in the first place.
So how do we determine $Q$ ?

4. Adaptive Range Finder. ${ }^{1}$

Given $m \times n$ matrix $A$, a tolerance $\epsilon$, and an integer $r$, find $Q$ such that

$$
\left\|\left(I-Q Q^{*}\right) A\right\| \leq \epsilon
$$

holds with probability at least $1-\min \{m, n\} 10^{-r}$.
Data: $A, \epsilon, r$
Result: $Q$
Draw standard Gaussian vectors $w^{(1)}, \ldots, w^{(r)}$ of length $n$.
for $i=1,2, \ldots, r$ do
$y^{(i)}=A w^{(i)}$
end
$\mathrm{j}=0$
$Q^{(0)}=[] ; \quad \quad / *$ the $m \times 0$ empty matrix $* /$
while $\max \left\{\left\|y^{(j+1)}\right\|,\left\|y^{(j+2)}\right\|, \ldots\left\|y^{(j+r)}\right\|\right\}>\epsilon / 10 \sqrt{2 / \pi}$ do
$\mathrm{j}+=1$
Overwrite $y^{(j)}=\left(I-Q^{(j-1)}\left(Q^{(j-1)}\right)^{*}\right) y^{(j)}$
$q^{(j)}=y^{(j)} /\left\|y^{(j)}\right\|$
$Q^{(j)}=\left[Q^{(j-1)} q^{(j)}\right]$
Draw a standard Gaussian Vector $w^{(j+r)}$ of length $n$.
$y^{(j+r)}=\left(I-Q^{(j-1)}\left(Q^{(j-1)}\right)^{*}\right) A w^{(j+r)}$
for $i=(j+1):(j+r-1)$ do
Overwrite $y^{(i)}=y^{(i)}-q^{(j)}\left\langle q^{(j)}, y^{(i)}\right\rangle$
end
end
$Q=Q^{(j)}$

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[^0]:    ${ }^{1}$ Algorithm 4.2 in Halko, Martinsson, Tropp, Page 25, http://arxiv.org/pdf/0909.4061.pdf

